## **Tactile Perception Design for Fabrication**

by

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## Abstract

High-resolution 3D printing technology provides the ability to manufacture shapes with precise geometry. Controlling this fine-scale geometry to confer haptic qualities is a growing area of research in fabrication. In this thesis, I will present three projects addressing the question of how to fabricate surface textures with controlled tactile properties and exploring how tactile textures can be used in custom manufacturing and to expand the understanding of the human sense of touch.

Surface roughness is one of the most significant qualities in haptic perception, essential to material identification, comfort, and usability. Past perceptual studies on roughness have typically used stimuli that are existing materials or in a narrow range of custom-made materials. In the first project presented in this thesis, we explore the use of 3D printing to manufacture stimuli. We used modeling and 3D printing to manufacture a set of fine parametric bump textures, and we used these texture stimuli in a psychophysical study of human roughness perception. We investigated the contribution of the texton spacing, size, and arrangement to the texture's perceived tactile roughness.

In the second project, we quantitatively address the problem of mapping arbitrary texture geometry to tactile roughness. Drawing from insights in past neurophysiology research, we developed a model that simulates human touch to predict a texture's tactile roughness from its surface geometry. We fabricated a set of 46 parametric and real-life textures, and we used psychophysical experiments with human subjects to place them in the perceptual space for tactile roughness using non-metric multidimensional scaling. We closely match this space with our quantitative model, obtained from strain fields derived from the elasticity simulations of the human skin contacting texture geometry. We demonstrate how this model can be applied to predict and alter surface roughness, and we show several applications in the context of fabrication.

The third project extends these ideas by developing a method to control a texture's haptic qualities and visual appearance at the same time. The tactile feeling and visual appearance of objects often interact in unpredictable ways, and both serve important purposes for identification and usability. In this project, we develop an optimization method to maintain a texture's visual appearance while altering its perceived tactile roughness or tactile temperature. Our optimization method, which is enabled by neural network-based models, allows us to change a texture to a different desired tactile feeling while preserving the visual appearance, at a relatively low computational cost.

# Contents

	Abs	tract .		ii
	List	of Figu	Ires	viii
1	Intr	oducti	on	1
	1.1	Backg	round	2
		1.1.1	Tactile perception	2
		1.1.2	Fabrication	3
	1.2	Contri	butions	5
<b>2</b>	Tac	tile Pe	rception of the Roughness of 3D-Printed Textures	6
	2.1	Introd	uction	6
	2.2	Metho	ds	8
		2.2.1	Texture Stimuli	8
		2.2.2	Subjects	11
		2.2.3	Psychophysical Procedures	12
		2.2.4	Data Analyses	13
	2.3	Result	S	14
		2.3.1	Experiment 1: Variable wavelength of isotropic textures, constant	
			texton size and shape	14
		2.3.2	Experiment 2: Anisotropic vs. isotropic textures of varying wavelength	20

		2.3.3	Experiment 3: Isotropic textures with constant wavelength, variable	
			texton size and shape	22
		2.3.4	Experiment 4: Interaction between texture wavelength and texton	
			dimensions	24
		2.3.5	How do subjects judge surface smoothness?	28
	2.4	Discus	sion and Conclusions	30
		2.4.1	3D printing technology yields better control of texture surface properties	31
		2.4.2	Papillary ridges as tactile processing units for textures	32
		2.4.3	Models of neural representation of textures	32
		2.4.4	Neural ensembles encode the spatial properties of textures $\ldots$ .	34
3	A O	uantit	ative Perceptual Model for Tactile Roughness	36
0	21	Introd	uction	37
	0.1	D		51
	3.2	Relate	d Work	38
		3.2.1	Tactile fabrication	39
		3.2.2	Psychophysics of roughness perception	40
		3.2.3	Haptic rendering	42
	3.3	Overvi	ew and Main Results	43
	3.4	Percep	tual Space	45
		3.4.1	Stimuli	45
		3.4.2	Experiments	48
		3.4.3	Data analysis	52
		3.4.4	Curved Surfaces	55
	3.5	Model	for Roughness	57
		3.5.1	Biological basis	57
		3.5.2	Simulation	58

		3.5.3	Computing variation	62
		3.5.4	Results	65
	3.6	Applie	cations	68
	3.7	Concl	usion $\ldots$	72
		3.7.1	Limitations and Future Work	74
	3.8	Chapt	er Notes	76
		3.8.1	Supplementary Material: Table of Textures	76
4	App	pearan	ce-Preserving Tactile Optimization	80
	4.1	Introd	luction	80
	4.2	Relate	ed Work	83
	4.3	Overv	iew	86
	4.4	Optim	nization	88
		4.4.1	Optimization Overview	88
		4.4.2	Tactile roughness	92
		4.4.3	Contact area	96
		4.4.4	Visual appearance	98
	4.5	Result	ts1	101
		4.5.1	Optimization results	101
		4.5.2	Evaluation and comparisons	.03
		4.5.3	Visual Experiments	.06
		4.5.4	Contact area experiments 1	.09
		4.5.5	Example applications	13
	4.6	Concl	usion	14
		4.6.1	Limitations and Future Work	16

<b>5</b>	5 Conclusion		
	5.1	Unsolved problems and future work	119
Bi	bliog	graphy	121

# List of Figures

2.1	Modeling process for isotropic textures: $\lambda$ is the wavelength of texture; d is	
	the texton diameter at the tip. The empty space between textons is equal to	
	the difference $\lambda$ -d. The modeling process allows for manipulation of texton	
	spacing, arrangement, and shape	10
2.2	Renderings of sample isotropic textures created with parametric modeling and	
	3D printing. These examples are comprised of raised truncated cones with	
	spherical caps of diameter = 0.3 mm. The illustrated wavelengths ( $\lambda$ ) range	
	from the smallest wavelength (0.625 mm) to the largest (1.375 mm) tested in	
	these experiments. The three reference wavelengths (0.75, 1.0, and 1.25 mm) $$	
	are also shown.	11
2.3	Subjects compared texture roughness using active touch. Two textures were	
	placed in a fitted case to be touched with digits 2 and 3 simultaneously	13
2.4	Psychometric curves plot the mean proportion of trials across all subjects in	
	which the reference texture [0.75 mm (red), $1.0$ mm (green), and $1.25$ mm	
	(blue)] is judged smoother than the comparison wavelength (+/-SEM). Sigma	
	values for $75\%$ threshold, exemplified by the dark arrows, are shown for each	
	reference wavelength. Smaller wavelengths are judged as smoother and have a	
	lower threshold value	15

2.5 A. Discrimination thresholds depend on texture wavelength. The three reference wavelengths plotted against their threshold values fit a line with slope 0.19, indicating a Weber fraction of 19%. B. Fingerprint ridge distance plotted against mean spatial sensitivity, defined as mean percentage of trials in which the smaller wavelength is judged smoother. Smaller fingerprint spacing is correlated with higher tactile acuity.

16

- 2.7 A: Experiment 2 compared anisotropic textures with textons oriented vertically or parallel to the edges of the texture plate; anisotropic textures with textons oriented diagonally (at 45 degrees) to the texture plate; and isotropic textures. The directions of texton alignment are shown by the yellow arrows. B. Anisotropic (regular) textures are generally judged smoother than isotropic textures when compared to the same set of 13 isotropic textures used in Experiment 1. Dashed psychometric curves and open symbols plot the mean proportion of trials across all subjects in which an anisotropic reference texture [0.75 mm (red), 1.0 mm (green), and 1.25 mm (blue)] is judged smoother than the comparison isotropic wavelength (+/-SEM). Solid curves and filled symbols replot the data from Fig. 4 in which both reference and comparison textures were isotropic. The preference for anisotropic textures is greatest for the largest wavelengths tested. B. Vertically oriented anisotropic textures are judged smoother than diagonally oriented textures of the same wavelength.
- 2.8 A: Sample 1.25 mm wavelength textures with flat textons of different sizes.

  a) Texture with small (0.1 mm diameter) textons; b) Texture with 0.3 mm textons; c) texture with large (0.5mm) textons. B: Comparisons between textons of different sizes in the three reference wavelengths. The smallest textons (like the 0.1 mm size shown with the magenta solid line) are judged the least smooth; larger diameter textons are judged progressively smoother, with the 0.5 mm size (red solid lines and filled red symbols) perceived as smoothest at all wavelengths. Flat textons feel smoother than rounded ones.

  23

21

2.9	Large diameter textons feel smoother than small diameter textons at all	
	wavelengths. Psychometric curves show comparisons of each of the 15 new	
	reference textures with flat-topped textons to the original standard set of 13	
	isotropic textures used in Experiment 1. Textons larger than the $0.3 \text{ mm}$	
	diameter rounded caps (red and gold traces) were judged smoother while those	
	of smaller diameter (blue and magenta traces) were judged less smooth for	
	all reference wavelengths. Flat-topped textons of the same diameter (green	
	curves) show nearly identical sensitivity as the rounded topped textons tested	
	in Experiment 1	25
2.10	Equivalencies between the flat texture elements and the rounded texture	
	elements are computed using the $0.5$ PSE of the psychometric curves in Figure	
	2.9. The two largest texton sizes in the $0.75 \text{ mm}$ reference wavelength are	
	omitted from this graph as they were judged smoother than all test textures	
	and therefore do not have a PSE	25
2.11	Relative magnitude estimates of smoothness of textures varying in wavelength	
	and texton diameter. The data from each psychometric function in Figure $2.9$	
	were averaged to obtain mean smoothness estimates for each wavelength and	
	texton size measured in Experiment 4	26
2.12	Judgments of relative smoothness of textures correlate with differences in	
	texton contact area (equivalent to texton density) on the skin; both are linked	
	to both texton diameter and texture wavelength. Data is re-plotted from	
	Figure 2.4. Although the individual data points are derived from pairs of	
	textures of different wavelengths, subjective perceptions of relative smoothness	
	appear to be independent of the specific wavelengths tested, but only upon	
	the relative areas of contact and blank spaces on the fingertips	28

2.13	Judgments of relative smoothness of textures depend upon differences in texton	
	contact area (A) and density (B) on the skin, which in turn are linked to both	
	texton diameter and texture wavelength. Data re-plotted from Figures 2.4,	
	2.8 and 2.9. Although the individual data points are derived from pairs of	
	textures of different wavelengths, subjective perceptions of relative smoothness	
	appear to depend upon differences in both wavelength and texton size, which	
	in turn modify the total contact area on the skin rather than the density of	
	contact points on the fingertips.	29
3.1	Given an input surface geometry, our model computes the tactile roughness	
	by computing skin deformation using elasticity simulations and sampling the	
	resulting compressive strain field. Our model enables the fabrication of tactile	
	objects with specified roughnesses.	36
3.2	Diagram of the structure of human skin (CNX (2017)). Roughness perception	
	is primarily mediated by Merkel cells, or SA1 receptors, located approximately	
	0.75 mm deep in the skin. $\ldots$	40
3.3	Modeling process for isotropic textures. The modeling process allows for	
	variation of texton arrangement, spacing $\lambda$ , and shape (here we control the tip	
	diameter $d$ )	47
3.4	Psychometric curves fit to percentage data, from our previous study. Errors	
	bars show SEM across subjects	49
3.5	The threshold of discrimination is proportional to the tested wavelength by a	
	factor of 0.19, known as the Weber fraction.	49

3.6	The standard scale of reference textures (numbers 1 through 13) depicted	
	along a logarithmic line scaled to the threshold of discrimination $\sigma$ . The	
	textures sample the perceptual space at a greater density than the threshold	
	of discrimination.	49
3.7	Seven examples of the 46 textures used in our experiments. Three bump	
	textures are shown with a green background, and four natural textures are	
	shown with a blue background. From left to right: standard bump texture	
	with wavelength 0.625mm; standard bump texture with wavelength 1.625mm;	
	flat bump texture with wavelength 1.0 and size 0.4 mm; foam; lizard skin;	
	stucco; knit wool. A list of all 46 textures is provided in the supplementary	
	material.	50
3.8	In a trial, participants were presented with three texture samples. They	
	touched each texture using the index finger and answered whether the leftmost	
	or rightmost sample felt more similar in roughness to the middle sample. $\ .$ .	51
3.9	The placement of our 46 texture samples in one dimension using the NMDS	
	algorithm. The number labels correspond to those in Figure 3.7 and in the	
	table in the supplementary material.	52
3.10	Left: cross-validation determines the optimal $\lambda$ value as 0.7. Right: most	
	of the variance is confined to the first dimension, indicating a good fit in	
	one-dimensional space.	54
3.11	Our curvature experiments tested the roughness of textured curved surfaces	
	with one of four curvatures (20 or 40 mm, concave or convex) against the	
	standard set of bump texture plates. Curved surfaces were textured with the	
	standard bump texture in one of three wavelengths	55

3.12 The points of subjective equality for all curved textures are plotted, with color indicating texture wavelength; the 19% threshold interval for each wavelength is indicated by the corresponding shaded intervals measured by the double arrows. All of the points of subject equality fall within their corresponding interval, indicating that the curved textures are judged equivalent in roughness to the corresponding flat texture of the same wavelength. . . . . . . . . .

57

- 3.13 a) The iterative process simulates the contact between the skin (blue) attached to a rigid bone (red) when the skin contacts a textured surface (gray). b) The simulation begins with an arbitrary contact area set using a threshold (constrained vertices are shown in green). The resulting boundary condition may be underconstrained, as many vertices fall below the contact area (shown in red). c) All vertices that fall beneath the boundary are constrained. However, some vertices (as shown in orange) may be over-constrained, or stretched. d) Over-constrained vertices are released from the boundary. After a number of iterations, the result converges to a stable contact boundary condition. . . . 61

3.16	For each texture simulation, the maximum compressive strain profile was	
	obtained for a depth of $0.75$ mm. To find the strain variation, pairs of sample	
	points (shown in red) were chosen from inside sampling areas (shown in yellow)	
	with radius $r$ separated by distance $d$ . The mean absolute difference of all	
	such pairs is defined to be the mean strain variation. Mean strain variation	
	was found to match perceptual estimates of roughness.	64
3.17	Comparison of roughness values found by four different methods suggested	
	in previous work $(R_a, 90$ th percentile, GLCM sum of squares, and GLCM	
	variance) and our method (strain variation). Our method produces the best	
	fit, with an $R$ value of 0.91. The bump textures are shown in green dots, and	
	the natural textures are shown in blue dots.	65
3.18	Left: the model is relatively insensitive to small changes in applied force, but	
	the fit worsens for large changes. Right: The model fit is relatively insensitive	
	to change in the choices of sampling distance and radius; the fit changes slightly	
	but still has a correlation over 0.85 for all values tested	66
3.19	Fit for the data excluding the five textures shown in red, which had significantly	
	higher variance in calculated roughness across the surface	67
3.20	For the three textures used in section 3.4, the percent difference in simulated	
	roughness was calculated between the flat texture and curved textures of	
	different radii. The percent difference is typically below the $19\%$ threshold	
	(the black dashed line), with the exception of very high curvatures (less than	
	10mm for concave surfaces, and less than 3mm for convex surfaces)	68
3.21	Two models, the gecko (left) and key cap (right), were fabricated with two	
	textures each. Fabricated models have height textures scaled to have different	
	tactile roughnesses, as matched against the standard set	69

3.22	a) Hedgehog with a rough bump texture that feels spiky; b) Screwdriver handle	
	with a moderately rough bump texture for easy and comfortable gripping; c)	
	Spinning "fidget ring" with rough cloud texture	70
3.23	From an original image (a), a depiction of a lion was created using two different	
	roughnesses to correspond to the colors (b). The fabricated model is shown in	
	(c). (The black image outlines are represented as smooth raised lines)	71
3.24	A representation of De Stijl-style geometric artwork (a) was created using	
	five different easily-distinguishable roughnesses (b) to represent the five colors.	
	The fabricated model is shown in (c). $\ldots$ $\ldots$ $\ldots$ $\ldots$ $\ldots$ $\ldots$	72
3.25	Textured plates with visual (left) or tactile (right) renderings. The top row	
	shows the rendered models; the middle row shows the 3D prints; the bottom row	
	shows a visual representation of the tactile strain map. The left panel shows	
	four texture plates with visible features that cannot be perceived tactually.	
	Conversely, the right panel shows the same four shapes which cannot be seen	
	but whose outlines can be felt, as seen in their strain profiles	73
3.26	Textures can be produced that contain hidden visual or tactual messages	73
4.1	Our optimization procedure enables the control of a texture's tactile roughness	
	while maintaining its visual appearance. Starting with a target texture (left),	
	the procedure optimizes toward a desired tactile roughness while preserving	
	the visual appearance (center). The resulting textures can be used to fabricate	
	visually similar but tactually different objects, such as these 3D-printed starfish	
	(right)	81
4.2	Parameter convergence during optimization for roughness and visual appear-	
	ance. The goal is to alter the roughness of the input texture (iteration 0) while	
	preserving its visual appearance, which is done by the final iteration. $\ldots$	91

4.3	a) When a significantly (10x) lower weight is used for $w_1$ , convergence of	
	roughness to the target may not occur. b) A significantly higher (10x) weight	
	for $w_1$ causes the visual energy to converge more slowly, and it may not reach	
	the target threshold.	91
4.4	In the original roughness model, a 3D FEM simulation was used to simulate	
	the skin touching a textured surface, and the maximum compressive strain	
	field was sampled from a depth of 0.75 mm.	92
4.5	a) Original random sampling; b) Equivalent deterministic sampling	94
4.6	Two examples from the test set of the learned CNN, showing learned and	
	ground-truth maximum compressive strain fields computed from heightmaps	
	(Strain fields are shown with rescaled contrast for visual clarity)	95
4.7	The difference in computed roughness between the learned strain field and the	
	real strain field is typically very low, with a median of $5.3\%$ .	96
4.8	The contact area function takes as input the input heightmap (left, red channel)	
	and the strain field (left, green channel) and outputs the distance field (center,	
	where black indicates a distance of $0$ ). The distance field can be used to	
	compute the contact area (right, where the contact area is black) $\ldots$ .	97
4.9	The learned contact area matches the actual contact area very closely, with an	
	error of 2.7%	97
4.10	A texture heightmap rendered with (center) or without (right) shadowing and	
	ambient occlusion. Shadowing in small regions of lowered height is critical to	
	a texture's visual appearance.	99
4.11	Plot showing render DSSIM and L2 difference errors for a set of textures in	
	optimization steps.	99

- 4.12 Two examples from the test set for visual rendering. The learned function for the rendering of heightmaps was learned with high accuracy: in most cases generated and real renderings are visually indistinguishable. . . . . . . . . 100
- 4.14 Seven example textures optimized for a desired roughness. The leftmost column shows the original, target visual texture; the next three columns show the results when the roughness is achieved through our optimization process; the final three columns show the results when the same roughness is achieved through linear scaling in the z and/or xy directions. The optimization process achieves the desired roughness with nearly-imperceptible changes to the visual 1024.15 Renderings of two textures optimized for different contact areas. 1044.16 Example of a texture cross-section for textures optimized for roughness. 104 4.17 Comparison of optimizing a texture to change contact area or scaling it to change contact area. The optimization results in smaller changes to the 1054.18 Comparison of modifying a texture's roughness by modifying the dominant

4.19	Heightmaps of the six textures used in visual experiments	107
4.20	The experimental setup for visual experiments, which allows the subject to	
	comfortably view the three trial textures from an overhead view	108
4.21	Top panel: Results from the experiments for each of our six textures. Bottom	
	panel: Proportions for all textures accumulated by JND distance from the	
	reference texture. The x-axis for each graph shows the distance in just-	
	noticeable-differences in roughnesses between the test texture and the reference,	
	and the y-axis shows the proportion judged the same. The dotted black line	
	shows the reference threshold at which subjects judged the reference textures	
	the same as each other	110
4.22	The results of one texture optimized for a lower (top) or higher (bottom) contact	
	area. From left to right: texture rendering, texture fingerprint, thresholded	
	finger contact, and simulated contact	111
4.23	Comparison of the experimental and simulated contact area of 36 textures. $% \mathcal{A} = \mathcal{A}$ .	111
4.24	Photograph of sets of bronze-cast textures used for tactile temperature ex-	
	periments (T3 and T5). Textures are ordered from less to more contact area.	
	Inconsistencies in appearance may be due to the manufacturing process and	
	polishing.	112
4.25	From left to right: textured models; models colored by roughness; photographs	
	of 3D-printed models. a) Two frogs textured with a tactile wood texture	
	optimized for different roughnesses. b) A bracelet with textured links that	
	have the same visual texture but have alternating roughnesses. c) A procedural	
	texture slider for a light switch, where the tactile roughness corresponds to	
	light intensity	115

4.26	Optimized textures applied to a surface with a radius of curvature of 5 mm.	
	The original texture (center) was optimized for a roughness 1 JND lower (left)	
	or 2 JND higher (right).	117

# Chapter 1

# Introduction

3D printing technology provides the ability to fabricate complex shapes with high precision. Users can fabricate customized models for a variety of purposes, from aesthetic objects, such as art or jewelry, to specific tools for specialized uses. Thousands of designs exist in online repositories such as Shapeways and Thingiverse, and users have the option of producing these models using a variety of materials and technologies, including filament-extrusion using thermoplastics; powder-binding (SLS or binder-jetting) using a broad range of powder materials; and projection stereolithography using photopolymer resin. With increasingly high resolution, new fabrication techniques allow the control of geometry at the scale of micrometers, with very little additional time needed to produce complex features.

Customizing the geometry of 3D models can create printable objects meeting a variety of mechanical and sensory purposes. Objects are often modeled at the large scale to accomplish a particular mechanical or aesthetic goal, but geometry can also be optimized on a more intricate scale to make physical models that accomplish other sensory goals subject to particular constraints, such as the goal of matching a visual appearance (Schüller et al. (2014), Elek et al. (2017)), achieving auditory properties (e.g. Umetani et al. (2016)) or matching tactile goals (Torres et al. (2015), Piovarči et al. (2016), Zhang et al. (2017)). This thesis

explores how the tactile properties of a 3D-printed model can be controlled by tuning its fine-scale surface geometry.

## 1.1 Background

#### **1.1.1** Tactile perception

Subjectively, tactile perception is made up of several "dimensions," including large-scale roughness, small-scale roughness, compliance, friction, and temperature (Tiest (2010), Hollins et al. (1993)). At a low level, these qualities elicit responses from various highly sensitive mechanoreceptors beneath the skin. Merkel cells at the base of the epidermis respond to strain, which is essential for detecting large-scale surface roughness (features over 0.1 mm) as well as compliance. The Pacinian corpuscle deep in the skin responds to vibrations, detecting small-scale roughness (under 0.1 mm) during active touch. The Meissner's corpuscle also plays a part in lower-frequency vibration detection during active touch. Cold and warm thermoreceptors in the skin respond to relative changes in temperature, and various muscle and skin-stretch receptors record the sense of proprioception, the body, skin and muscle positions, which informs perception of friction and compliance during touch. Of the tactile dimensions, roughness is generally known as the most important and apparent when identifying surfaces. It is used to identify material composition and comfort, and it is particularly essential for manual dexterity, as it serves as a cue for grip force and orientation in manual tasks (Johansson and Westling (1984)).

The relationship between a material, its surface geometry, and tactile perception is intricate, which makes the task of producing and designing tactile properties difficult. For other senses, such as sight and hearing, widely-accepted models exist, and these models have been used for visual and audio synthesis for some time. However, the understanding of the sense of touch is less mature, and methods of producing objects with a defined tactile feel are still in early stages.

A major reason that the sense of touch is less understood than other senses is the difficulty in producing controlled stimuli for psychophysics studies. A range of compliant objects can be produced with some difficulty using, for example, mixes of rubbers (Tiest and Kappers (2009a)). Thermal perception can be controlled using a Peltier thermoelectric element to heat or cool the skin (Ino et al. (1993)). However, producing stimuli to study roughness is less straightforward. Many past studies in roughness perception have used existing "natural" stimuli such as sandpapers (Hollins and Risner (2000)), paper and fabric (Manfredi et al. (2014);Weber et al. (2013)), and other everyday items. These types of materials vary greatly among several dimensions and are difficult to quantify. Conversely, some studies have used a narrow range of artificial stimuli, such as gratings (Lederman (1974)) or shallow bump textures typically made with photo-embossing (e.g. Yoshioka et al. (2001) and Connor et al. (1990)). These artificial stimuli have significant limitations, as they are unnatural and have limited resolution. Here we posit that studies of tactile perception can be greatly aided by the production of single-material stimuli encompassing a full range of geometries and tactile properties, which is increasingly possible using 3D printing technologies.

#### 1.1.2 Fabrication

Traditionally, the tactile feeling of 3D-printed objects has been dictated by the base material used: for example, different materials have different surface finish, compliance, and perceived temperature. The manufacturing process plays a role as well: filament-extrusion, for example, typically produces a ridged surface finish according to the filament and layer size; powder-binding produces objects with a fine-scale grainy surface and due to the base powder; and stereolithography produces a smoother finish due to its thinner layers and light bleed. All of these technologies can produce tactile objects with some range of tactile properties based on the input's surface and internal geometry, although the scale and possibilities for that geometry is dependent on the printer or manufacturing process.

In most applications, altering an object to produce tactile properties has typically been done qualitatively, for example, by letting a user select a visual textured displacement map or choose an infill that provides some degree of relative softness (e.g. Torres et al. (2015)). Varying surface geometry to control roughness is fairly common in conventional manufacturing, such as injection molding for plastic, or knurling in CNC machining, but the tactile feeling is similarly not quantified.

In custom objects, varying small-scale geometry to control tactile feeling is still an area of early research, in part because 3D printers with high enough accuracy and precision have not been widely available until recently. Some recent work has used 3D printing to create surfaces with quantifiable tactile properties: for example, tactile compliance can be controlled in a multi-material printer using combinations of different rubber-like materials of different softness (Piovarči et al. (2016)); and 3D printed hair or bristle structures can be used to produce different percepts of roughness and compliance as quantified against common materials (Degraen et al. (2019)).

In the works presented here, we describe methods to produce objects with precise surface geometry in order to control their tactile roughness and, to an extent, tactile temperature. To produce these models, we use the B9Creator, a low-cost projector digital light processing (DLP) stereolithography printer, which has a resolution of 50 microns and a z-layer height of 30 microns; because of light bleed and smoothing, the smallest features possible with this printer are at the scale of 200 microns. Models are made of a single material, and we control tactile properties using only the changes in surface geometry.

## **1.2** Contributions

This thesis addresses the questions how to use 3D printing to produce better sensory stimuli, and how to enable tactile properties for custom manufacturing. This thesis summarizes my efforts to bridge the space between between the use of geometric modeling and fabrication, and the research of sensory neurophysiology and subjective perception.

In Chapter 2, we produce fine, customized 3D-printed bump texture models to explore and quantify tactile roughness perception in a parametric space. Chapter 3 explores roughness perception of a larger variety of natural texture geometries, and uses insights from research in neurophysiology to develop a skin simulation-based model to predict a surface's tactile roughness and enable the creation of tactile objects. Chapter 4 develops a method to speed up the roughness computation by replacing the slow FEM simulation with faster neural-network based approach. This speedup enables optimization of textures to preserve their appearance while achieving a target surface roughness, and a similar method can be used to control contact area, which alters the perceived temperature of the surface.

# Chapter 2

# Tactile Perception of the Roughness of 3D-Printed Textures

Here we use a set of parametrically designed 3D-printed textures to investigate the tactile perception of roughness. This chapter is based on the publication Tymms et al. (2017), in collaboration with co-authors Denis Zorin and Esther P. Gardner. I designed and manufactured the stimuli, collected the experimental data, processed the data and performed the statistical analyses. Denis Zorin and Esther P. Gardner took part in designing the study and writing the paper, and Esther P. Gardner and I performed the data analysis.

## 2.1 Introduction

Roughness is an integral property of tactile perception. Roughness perception is essential for judging material composition; it informs the perception of important properties like comfort and friction and aids manual dexterity, such as using appropriate grip force for object manipulation (Johansson and Westling (1984); Bilaloglu et al. (2015)).

Many studies on roughness perception have been conducted in the past using stimuli

such as Braille dots, photo-etched dot arrays, gratings, and natural or manufactured surfaces. However, due to an inability to produce specific and finely controllable stimuli, few of these studies have provided a comprehensive examination of a variety of surfaces, nor the parametric features that give rise to sensations of roughness.

Physically, the term roughness refers to height differences on the surface, which can be described in a number of ways in terms of surface geometry. The dimensions of the surface elevations that form textures — here called "textons"— are a key feature of textured surfaces. Textons can be uniform in shape, height, and surface area, such as hemispherical Braille dots (Phillips et al. (1990)), ridges of rectilinear gratings (Lederman and Taylor (1972); Lederman (1974); Phillips and Johnson (1981); Lederman et al. (1982); Sathian et al. (1989); Sinclair and Burton (1991); Cascio and Sathian (2001); Yoshioka et al. (2001)), truncated cones used in dot arrays (Connor et al. (1990); Connor and Johnson (1992); Phillips et al. (1992); Klatzky and Lederman (1999); Meftah et al. (2000); Hollins (2001); Chapman et al. (2002); Smith et al. (2002); Dépeault et al. (2009); Eck et al. (2013)), or the threads of textiles (Manfredi et al. (2014); Weber et al. (2013)). Irregular textons include many natural materials, animal skins, and sandpapers (Hollins et al. (1993); Hollins and Risner (2000); Tiest and Kappers (2006); Bilaloglu et al. (2015)). The physical dimensions of individual textons define the microstructure of a textured surface.

Similarly, the density and arrangement of textons define texture macrostructure. Textons can be arranged in regular patterns characterized by specific spacings (anisotropic arrays), or in seemingly random arrangements that can be defined by a characteristic mean spacing between textons (isotropic arrays). The macrostructure of regular arrays is easily seen in geometric patterns such as rectangular or hexagonal grids of specific size. In this manner, textures can be treated mathematically in terms of texton area, spacing and arrangement on the surface (Fig. 1).

Perceptually, the term "roughness" is somewhat imprecise. Generally, a rough surface

causes uneven pressure on the skin when touched statically and elicits vibrations when stroked (Connor et al. (1990); Hollins et al. (1993); Hollins and Risner (2000); Tiest (2010); Manfredi et al. (2014)). However, the underlying physiological mechanisms are complex. The skin of the human hand is non-uniform in thickness and contains four different types of mechanoreceptors that mediate tactile sensations of spatial distribution, vibration, and skin stretch; this low level processing is followed by higher-level neural coding in the CNS. Furthermore, texture perception has three distinct dimensions (rough/smooth, hard/soft, and slippery/sticky) that interact in complex ways (Hollins and Risner (2000); Picard et al. (2003); Yoshioka et al. (2007); Callier et al. (2015)).

In this study we use three-dimensional (3D) printing to create textures with investigatordefined surface properties. 3D printing provides the ability to rapidly fabricate objects with user-defined shape and surface features at low cost with high resolution and accuracy. We created a range of finely textured surfaces with varying surface properties: surface textons differ in spacing (0.6-1.4 mm), diameter (0.1-0.5 mm), shape (rounded or flat-topped), and alignment (anisotropic or isotropic). We conducted four psychophysical studies exploring the contribution of these parameters to roughness perception. We report that 1) large wavelengths and small texton sizes produce higher estimates of roughness; 2) regularly arranged anisotropic textures are perceived as slightly smoother than isotropic textures of the same wavelength; and 3) the area or density of texton skin contact is correlated with surface smoothness.

# 2.2 Methods

#### 2.2.1 Texture Stimuli

The textures used for the experiments were created using 3D modeling and fabricated from plastic using a 3D printer. They consist of flat plates with raised dot-like textons shaped as truncated cones with flat or spherical caps. The patterns vary in element spacing, size, shape, and alignment. These types of stimuli are common in texture experiments and were chosen because the parameters can be easily and consistently manipulated to create a variety of textures.

#### 2.2.1.1 3D Modeling

Texture patterns were created as height maps with specified spatial periods or wavelengths  $(\lambda)$ , arrangement, and texton shape. The texture wavelength specifies the center-to-center distance between neighboring textons, and defines the texture *macrostructure*. The textures used in this study varied in wavelength from 0.6 to 1.4 mm. In isotropic arrays, such as those illustrated in Figures 2.1 and 2.2, the wavelength specifies the mean distance between textons in all directions. The textures used in this study varied in wavelength from 0.6 to 1.4 mm. In a rectangular grid anisotropic texture, as illustrated in Figure 2.7A, the spacing between textons is uniform along the horizontal and vertical axes, and when rotated 45 degrees to a tetragonal diamond array, the wavelength along the horizontal and vertical axes is larger by a factor of  $\sqrt{2}$ .

The texture *microstructure* is defined by the texton geometry. In this study we created textons shaped as truncated cones, with either flat tops of diameter (d) 0.1 to 0.5 mm, or round hemispheres of d = 0.3 or 0.5 mm. All textons on an individual surface had uniform dimensions (tip shape and diameter). All textons had a height h = 1.0 mm above the base plate.

The 3D modeling procedure used to specify isotropic textures is schematized in Figure 2.1. First, a Fourier magnitude spectrum was created for each texture. This matrix represents the magnitude component of the Fourier transform of the image. For random textures, the resulting texture will have one dominant wavelength over all directions; this magnitude spectrum is visualized as the outline of a circle with a radius given by  $s/\lambda$ , where s is the



Figure 2.1: Modeling process for isotropic textures:  $\lambda$  is the wavelength of texture; d is the texton diameter at the tip. The empty space between textons is equal to the difference  $\lambda$ -d. The modeling process allows for manipulation of texton spacing, arrangement, and shape.

pixel size of the image and  $\lambda$  is the dominant wavelength (Figure 2.1a).

We then take the 2D inverse Fourier transform using the magnitude and a random phase matrix. For an isotropic texture, the resulting pattern (Figure 2.1b) has a random noise-like appearance with maxima spaced according to the dominant wavelength. The relative maxima of the 2D inverse Fourier transform is transformed into an analogous bump texture by inserting the texture elements, e.g. truncated cones, at these peak locations. The resulting textured surface has textons arranged with an average spacing of the specified wavelength (Figure 2.1c and 2.1d). Isotropic textures of this sort served as the comparison stimuli in most of the experiments described below.



Figure 2.2: Renderings of sample isotropic textures created with parametric modeling and 3D printing. These examples are comprised of raised truncated cones with spherical caps of diameter = 0.3 mm. The illustrated wavelengths ( $\lambda$ ) range from the smallest wavelength (0.625 mm) to the largest (1.375 mm) tested in these experiments. The three reference wavelengths (0.75, 1.0, and 1.25 mm) are also shown.

#### 2.2.1.2 Texture Fabrication

The textures we specified were embossed on square plates 25 mm on each side. They were fabricated from plastic using a digital light processing stereolithography 3D printer with  $50\mu m$  pixel resolution (B9Creator v1.2).

The first experiment used isotropic (random) textures with sphere-capped textons of diameter = 0.3 mm arranged with different spatial periods. Three spatial periods were chosen as reference wavelengths: 0.75 mm, 1.0 mm, and 1.25 mm. These three wavelengths were compared to other isotropic textures ranging from wavelength  $\lambda = 0.625$  to 1.375 mm. In subsequent experiments, the comparison isotropic textures were tested against anisotropic textures (regularly aligned texton grids) of wavelengths = 0.75 mm, 1.0 mm, and 1.25 mm, and 1.25 mm, and 1.25 mm, and to textures with textons of various tip sizes and shapes.

#### 2.2.2 Subjects

The study was approved by the New York University Committee on Activities Involving Human Subjects (IRB). All subjects signed informed consent forms prior to the study. Sixteen paid subjects (8 male and 8 female, 21-35 years old) participated in the experiments. All selfidentified as strongly right-handed according to the survey used in Chapman and Chapman (1987), and all reported normal sensory and motor ability of the hands and fingers. Each subject participated for up to four hours of trials spread over at least two sessions, which resulted in a total of 600 to 800 pair comparisons. Each subject was free to terminate a session or withdraw from the study at will. Subjects were also asked to provide fingerprints after completing the trials.

#### 2.2.3 Psychophysical Procedures

The experiments conducted followed two-alternative forced-choice discrimination protocols using free, active touch. Subjects were instructed to scan the surfaces using natural exploratory movements to discern their surface properties (Callier et al. (2015)). As surface texture plays an important role in haptic identification of objects, and humans generally move their hands over the surface of test objects during exploratory procedures (Lederman and Taylor (1972); Lederman and Klatzky (1987)), we concluded that free, active touch is an appropriate manner for subjects to rate the smoothness of textures.

In each trial, a subject was presented with a reference texture and a test texture. The two texture plates were placed inside a 3D-printed plastic case designed to fit the texture plates, as shown in Figure 2.3. The case was appended firmly to a table to prevent any motion. The subject sat in a chair facing the table and was instructed to feel the two stimuli using a stroking motion in the proximal direction (towards the body) with the index and middle fingers (digits 2 and 3) of the right hand. Subjects were free to orient their body at the angle that was most comfortable for stroking in a proximal direction. The ordering of the trials was randomized, and the positions of the two stimuli were switched equally to avoid bias in positioning.

Before each trial, an audio tone was played to indicate to the subject that the pair of stimuli was ready for the trial to begin. Trials were self-initiated: the subject pressed the right and left arrow keys on a provided keyboard with their left hand to record when they



Figure 2.3: Subjects compared texture roughness using active touch. Two textures were placed in a fitted case to be touched with digits 2 and 3 simultaneously.

began touching the stimuli. The subject was asked to indicate which texture (left or right) felt smoother by releasing the left or right arrow key. The subject could take as long as needed, and the time taken to palpate the texture and make a decision (i.e., the time between pressing down the two arrow keys and releasing one arrow key) was recorded. Subjects typically stroked the textures repeatedly before making a decision. We did not provide feedback to subjects about performance, as the goal of this study was to determine the physical parameters of textures underlying percepts of smoothness. We assumed that texture pairs were perceptually equivalent if one was rated smoother in 50% of trials, and pairs were perceptually distinct if one was rated smoother in 75% or more of trials.

We included a set of practice trials as the beginning of each session to familiarize subjects with the mechanics of the task and to ensure that they understood the task instructions. Subjects were asked to close their eyes during the trials, and white noise was played for the duration of the experiment in order to mask auditory cues.

### 2.2.4 Data Analyses

Paired t-tests (ttest, MATLAB r2014a) were used for the data of Experiment 1 to assess the differences in tactile sensitivity and ridge size between the fingers. ANOVA protocols: For the anisotropic textures used in Experiment 2, an N-way analysis of variance (anovan, MATLAB r2014a) was applied to the data across all subjects for each reference texture. Analysis was applied for two different types of pairs of groups: isotropic vs anisotropic references, and anisotropic vertically aligned vs anisotropic diagonally aligned reference textures. The test texture was used as additional grouping variable, with the proportion judged smoother as the Y-value in order to determine whether groups were significantly different across the test wavelengths. The level of significance was set at P < 0.05 for these analyses.

## 2.3 Results

# 2.3.1 Experiment 1: Variable wavelength of isotropic textures, constant texton size and shape

The first experiment addressed the question of how the spatial period of randomly arranged texture elements affects the texture's perceived roughness or smoothness. Stimuli were pairs of isotropic (random) textures with sphere-capped texture elements of diameter 0.3 mm arranged with different spatial periods. Three spatial periods were chosen as reference wavelengths: 0.75 mm, 1.0 mm, and 1.25 mm. These three wavelengths were compared against all other isotropic textures ranging from wavelength 0.625 to 1.375 mm in 0.0625 mm intervals (see Figure 2.2 for examples). To maximize meaningful data, more comparisons were performed between more similar textures and fewer comparisons between more easily distinguishable stimuli. Sixteen subjects participated in this experiment, and each performed between four and twenty trials for each texture pair.

The cumulative results from all subjects with respect to the three reference stimuli are shown in Figure 2.4. This figure shows the mean proportion of trials in which the reference texture was judged smoother than the test texture. For each reference texture, a psychometric



Figure 2.4: Psychometric curves plot the mean proportion of trials across all subjects in which the reference texture [0.75 mm (red), 1.0 mm (green), and 1.25 mm (blue)] is judged smoother than the comparison wavelength (+/-SEM). Sigma values for 75% threshold, exemplified by the dark arrows, are shown for each reference wavelength. Smaller wavelengths are judged as smoother and have a lower threshold value.

curve was fit to the data using the Wichmann and Hill psychometric function (Wichmann and Hill (2001)), which is a cumulative Gaussian function with additional parameters for guess and lapse rates. The function is of the form

$$y = g + 0.5 * (1 - g - l)(1 + \operatorname{erf}((x - u)/\sqrt{2v}))$$

, where g is the guess rate, l is the lapse rate, u is the mean and v is the standard deviation; erf is the normal error function. The threshold of discrimination  $\sigma$  for each psychometric curve is defined as the difference in wavelength at which the psychometric function crosses the 75% confidence interval (see Figure 2.4A).

For all pairs of textures, subjects typically rated the surface with the smaller wavelength (and greater density of textons) as smoother than the surface with the larger wavelength, although the proportion varied according to the compared wavelength. For example, the reference wavelength 0.75 mm was judged as smoother in 99% of trials when compared to a



Figure 2.5: A. Discrimination thresholds depend on texture wavelength. The three reference wavelengths plotted against their threshold values fit a line with slope 0.19, indicating a Weber fraction of 19%. B. Fingerprint ridge distance plotted against mean spatial sensitivity, defined as mean percentage of trials in which the smaller wavelength is judged smoother. Smaller fingerprint spacing is correlated with higher tactile acuity.

test wavelength 1.25 mm, and it was judged smoother in 86% of trials when compared to test wavelength 1.0 mm; when compared to a smaller test wavelength 0.625 mm, it was judged smoother in only 23% of trials. Likewise, the 0.75 mm reference was always rated smoother than the other references for each comparison, the 1.0 mm reference was judged intermediate in smoothness, and the 1.25 mm reference was rated as least smooth.

The smoothness of surfaces is proportional to the density of the texture elements; when more textons contacted the skin, the surfaces felt smoother to subjects. By analogy, roughness seems to be correlated with greater texton spacing or wavelength within our range of spacings (less than 1.4 mm), suggesting that the extra distance enables each texton to more effectively indent the skin and elicit an abrasive sensation. These observations are consistent with previous studies modeling receptor responses of tactile afferents (Vega-Bermudez and Johnson (1999)).

Figure 2.5A shows the three reference wavelengths plotted against their  $\sigma$  threshold of discrimination values. The thresholds scale proportionally to the reference wavelengths,
indicating that the threshold of discrimination is lower and thus better for smaller wavelengths than for larger wavelengths. The values fit a line with a slope of 0.19. This slope is known in psychophysics as the Weber Fraction, and the value is consistent with previous work that found the Weber Fraction for roughness discrimination between 0.1 and 0.38 (Hollins and Bensmaïa (2007)).

Figure 2.5A also indicates some variation in the discrimination thresholds of individual subjects. Previous studies by Peters et al. (Peters et al. (2009)) demonstrated that acuity of tactile perception of surface detail corresponds to the distance between the fingerprint ridges, as SA1 afferents are distributed along the centers of the papillary ridges of the finger. To test this hypothesis, we asked subjects to provide samples of their fingerprints after participating in the experiment. The fingerprint images were scanned and analyzed for ridge frequency using the techniques presented in Kovesi (Kovesi (2005)) based upon methods developed by Hong et al. (Hong et al. (1998).

Of the sixteen subjects tested, four subjects' fingerprints could not be analyzed reliably according to the algorithm. For the remaining subjects, the median ridge frequency is plotted against the subjects' mean performance accuracy across all comparison pairs (Figure 2.5B). We found that the mean papillary ridge spacing of each subject's fingerprints ( $0.398 \pm 0.003mm$ ) is inversely correlated with the overall proportion of trials in which they judged the smaller wavelength as smoother (mean spatial sensitivity =  $0.833 \pm 0.0041$ ). The data fall around a line with a negative slope, meaning that subjects with smaller papillary ridge distance tended to show higher accuracy in tactile smoothness perception; differences between male and female subjects in this pool were not significant (P = 0.48), nor were differences between D2 and D3 (P = 0.34). These findings support the idea that smaller papillary ridge spacing is linked to higher tactile sensitivity, possibly due to a greater density of SA1 Merkel cell receptors lying along the center of each papillary ridge. Combined with the Weber fraction measurements in panel 2.5A, the data in panel 2.5B indicate that subjects are capable of discriminating pairs of textons spanning adjacent papillary ridges.

#### 2.3.1.1 Tactile sensitivity differs between fingers

We also noted that textures of similar wavelengths were often rated as smoother when tested on digit 2 than on digit 3. The heat map in Figure 2.6A indicates the mean proportion of trials in which subjects rate the texture presented to D2 as smoother than the texture presented to D3. The vertical axis shows the stimulus wavelength presented to the subject's digit 2 (D2), and the horizontal axis shows the wavelength presented beneath digit 3 (D3). The values and corresponding colors represent the corresponding proportion of trials in which the D2 stimulus was judged smoother. When textures are similar in wavelength (along the diagonal), it is apparent that subjects were biased toward judging the texture under digit 2 as smoother, as indicated by the red coloration.

We found similar biases towards digit 2 across all of the reference textures tested. The bar graphs in Figure 2.6B and 2.6C illustrate the choice probability on individual trials as a function of the difference in wavelength between the D2 and D3 stimuli. Textures that differ in wavelength by <0.5 mm are identified as smoother with greater reliability when the smaller wavelength is applied to D2 for the entire range of wavelengths tested.

Not only do the subjects show a tendency to select the D2 stimulus as smoother when the wavelengths differ by <0.5 mm, but their decision time is shorter, suggesting that they are more certain of the accuracy of the judgment (Figure 2.6C). When the texture wavelengths differ by more than 0.5 mm, the subjects' responses occur at latencies of 3 s. However, difficult decisions take more than 5 s, and take longer when the smaller wavelength is presented to D3.

As the reference and comparison stimuli were tested equally often on digits 2 and 3, the mean smoothness estimates shown in Figure 2.4 reflect the discriminability parameter d' and its performance cognate (PCmax) computed by the method of McFadden (McFadden (1970);



Figure 2.6: A: Heat map comparing the proportion of judgments for each stimulus pair. In general, the D2 stimulus is judged smoother more often (red) than the D3 stimulus (blue) when the textures differ in wavelength by <0.5 mm; at wider spacing veridical judgments predominate (upper right and lower left corners). B: Stimulus pair wavelength difference plotted against mean sensitivity, defined as the proportion of trials in which subjects judged the smaller wavelength as smoother. The graph skews to the left, indicating that the D2 stimulus is judged smoother a higher proportion of the time. C: Stimulus pair wavelength difference plotted against the mean subjective reaction time in the trial. The graph skews right, indicating that subjects spend more time deciding when the D3 stimulus has the smaller wavelength. These graphs indicate that subjects are biased toward feeling the D2 stimulus as smoother.

Gardner and Johnson (2012)).

## 2.3.2 Experiment 2: Anisotropic vs. isotropic textures of varying wavelength

Given the correlation of perceived smoothness with texture wavelength, we also examined the relation between perceived smoothness and the irregular spacing of textons in the isotropic textures tested in Experiment 1. We fabricated two new sets of anisotropic reference textures with wavelengths  $\lambda = 0.75$  mm, 1.0 mm, and 1.25 mm, with the same 0.3 mm sphere-capped textons. Textons were arranged regularly in a rectangular grid with one of two rotations: a) with textons aligned to the edges of the square, and b) with the texture pattern rotated diagonally at a 45 degree angle (Figure 2.7A). The new anisotropic stimuli were used as references and compared against the same thirteen isotropic textures tested in Experiment 1. Seven subjects participated in the experiment and each performed between two and ten comparisons per stimulus pair, with a greater number of comparisons for more similar stimulus pairs.

The lower panels of Figure 2.7 show the data and corresponding psychometric curves for experiments in which anisotropic reference textures oriented in either direction were compared against the isotropic textures used in Experiment 1 (dashed lines, open symbols). Both vertically and diagonally aligned anisotropic textures showed similar trends to the isotropic textures: wavelengths with small spacing were judged smoother than those of large wavelengths, and smaller wavelengths had a greater slope and thus a better threshold of discrimination. Anisotropic textures were generally rated smoother than isotropic textures of the same wavelength (Figure 2.7B), and the judgments were significant for the two larger wavelengths tested, 1.25 mm and 1.0 mm (P = 0.006 and P = 0.0304, with F = 7.66 and F = 4.8, respectively). When  $\lambda = 0.75$  mm, anisotropic and isotropic textures did not differ



Figure 2.7: A: Experiment 2 compared anisotropic textures with textons oriented vertically or parallel to the edges of the texture plate; anisotropic textures with textons oriented diagonally (at 45 degrees) to the texture plate; and isotropic textures. The directions of texton alignment are shown by the yellow arrows. B. Anisotropic (regular) textures are generally judged smoother than isotropic textures when compared to the same set of 13 isotropic textures used in Experiment 1. Dashed psychometric curves and open symbols plot the mean proportion of trials across all subjects in which an anisotropic reference texture [0.75 mm (red), 1.0 mm (green), and 1.25 mm (blue)] is judged smoother than the comparison isotropic wavelength (+/-SEM). Solid curves and filled symbols replot the data from Fig. 4 in which both reference and comparison textures were isotropic. The preference for anisotropic textures is greatest for the largest wavelengths tested. B. Vertically oriented anisotropic textures are judged smoother than diagonally oriented textures of the same wavelength.

significantly, suggesting that subjects were unable to distinguish jitter in the position of the textons at such small wavelengths, when textons contacted neighboring papillary ridges.

Additionally, vertically aligned textures were generally judged smoother than diagonally aligned textures (Figure 2.7C), but the difference was significant only for the 1.25 mm wavelength (P = 0.005, F=8.46). This finding supports the suggestion that texture spacing, specifically with respect to the direction of motion, influences estimates of roughness, as textures oriented diagonally have a slightly larger spacing (i.e.  $\lambda\sqrt{2}$ ) along the path of motion (Connor and Johnson (1992)). The difference may be attributable to the different frequency of vibrations elicited by the different arrangements when stroked vertically.

The difference between these textures was more pronounced for the larger wavelengths, suggesting that when texture features are dense, differences in arrangement may become less easily discernable. Dense features may be more difficult to distinguish because mechanore-ceptors have a limited ability to resolve spatial detail. In particular, the SA1 afferents can differentiate spatial detail down to 0.5mm (Johnson (2001)), so features arranged near that minimum distance might be more difficult to resolve. Similarly, sensitivity to vibration differs at different frequencies, so the differences in vibrations may be more noticeable for the larger wavelength.

# 2.3.3 Experiment 3: Isotropic textures with constant wavelength, variable texton size and shape

Experiments 1 and 2 assessed the effect of texture wavelength and texton density and orientation on judgments of smoothness. All of the textures were comprised of 0.3 mm diameter rounded textons. In Experiment 3, we assessed the effect of texton diameter and shape on perceptions of smoothness by varying these parameters while maintaining a constant the wavelength and texton density. We fabricated a new set of textures with flat-topped



Figure 2.8: A: Sample 1.25 mm wavelength textures with flat textons of different sizes. a) Texture with small (0.1 mm diameter) textons; b) Texture with 0.3 mm textons; c) texture with large (0.5mm) textons. B: Comparisons between textons of different sizes in the three reference wavelengths. The smallest textons (like the 0.1 mm size shown with the magenta solid line) are judged the least smooth; larger diameter textons are judged progressively smoother, with the 0.5 mm size (red solid lines and filled red symbols) perceived as smoothest at all wavelengths. Flat textons feel smoother than rounded ones.

truncated cone shaped textons of diameter 0.1, 0.2, 0.3, 0.4, and 0.5 mm, and rounded sphere-capped elements with diameter 0.3 or 0.5 mm (Figure 8A). Wavelengths of 0.75mm, 1.0mm, and 1.25mm were chosen as references for each set of textures. Each texture was compared against all other textures of the same wavelength using our standard two-alternative forced choice protocol.

Results were fit with psychometric curves, and are shown in Figure 2.8B. The left column shows the comparisons between flat texton shapes of a given wavelength, and the right column shows the comparison between round texton shapes alongside the flat shapes of the same wavelength. At each reference wavelength and at each texton diameter, textons with the larger diameter textons of each pair were judged smoother. The largest-diameter textons tested (0.5 mm) were judged smoother than all other sizes tested; likewise surfaces with the smallest-diameter textons (0.1 mm) were perceived as roughest (least smooth).

Likewise, textures with rounded caps, as indicated by the dashed lines and empty circles in Figure 2.8B, right column, are judged as slightly less smooth than the same diameter texton with a flat cap. This expands on the theory that the sensation of roughness or abrasiveness is caused when textons effectively indent the skin. Thus, more sharply pointed elements feel rougher, while flatter elements feel smoother.

## 2.3.4 Experiment 4: Interaction between texture wavelength and texton dimensions

Given the investigation of texture element shape and spacing, the next natural question to ask is how combinations of different texture shapes and wavelengths relate to each other perceptually. The stimuli in this experiment were a combination of the stimuli from Experiments 1 and 3. The reference stimuli were the flat-texton stimuli from Experiment 3 manufactured with three reference wavelengths (0.75 mm, 1.0 mm, and 1.25 mm). The test



Figure 2.9: Large diameter textons feel smoother than small diameter textons at all wavelengths. Psychometric curves show comparisons of each of the 15 new reference textures with flat-topped textons to the original standard set of 13 isotropic textures used in Experiment 1. Textons larger than the 0.3 mm diameter rounded caps (red and gold traces) were judged smoother while those of smaller diameter (blue and magenta traces) were judged less smooth for all reference wavelengths. Flat-topped textons of the same diameter (green curves) show nearly identical sensitivity as the rounded topped textons tested in Experiment 1.



Figure 2.10: Equivalencies between the flat texture elements and the rounded texture elements are computed using the 0.5 PSE of the psychometric curves in Figure 2.9. The two largest texton sizes in the 0.75 mm reference wavelength are omitted from this graph as they were judged smoother than all test textures and therefore do not have a PSE.



Figure 2.11: Relative magnitude estimates of smoothness of textures varying in wavelength and texton diameter. The data from each psychometric function in Figure 2.9 were averaged to obtain mean smoothness estimates for each wavelength and texton size measured in Experiment 4.

stimuli were the comparison isotropic textures used in Experiments 1 and 2; their wavelengths varied from 0.625 mm to 1.375 mm, and textons were 0.3 mm diameter rounded cones. To maximize significant data in this experiment, fewer comparisons were performed between more obviously different textures. Five subjects participated in this experiment, and each performed on average four comparisons per texture pair.

Figure 2.9 shows psychometric curves for the five texton sizes at the three reference wavelengths. Results indicate that textures with larger texton sizes feel smoother at all wavelengths. Surfaces with textons larger than the reference 0.3 mm size were judged smoother than the comparison reference texture regardless of wavelength. Likewise, surfaces with textons smaller than the reference 0.3 mm values were judged less smooth, as the psychometric functions crossed the 75% threshold level at greater wavelengths than the reference values.

To further analyze the interaction of texton spacing (i.e., wavelength) and texton diameter on perceptions of smoothness, we defined the Point of Subjective Equality (PSE) for each psychometric function in Figure 2.9 as the wavelength whose roughness is estimated as 0.5. In other words, the PSE is the estimated wavelength judged as most equal to the reference stimulus; the computed PSE values for the whole set of textures compared in this experiment are plotted in Figure 2.10. For example, the reference texture with wavelength 0.75 and flat texton d = 0.1 mm has a PSE of 0.855 mm, meaning that the psychometric curve crosses the 50% threshold at x = 0.855. Therefore, this texture is judged similar in smoothness to a test texture with rounded 0.3 mm elements of wavelength 0.855 mm. Likewise, the 1.25 mm reference texture of flat texton d = 0.5 mm feels equivalent to the 1.0 mm wavelength comparison texture.

The PSE data indicate that increasing the texton diameter is equivalent to decreasing the texture wavelength, that is, reducing the spacing between textons. Likewise, decreases in texton diameter decreases estimates of smoothness, and are therefore perceived as rougher surfaces.

To assess the relative contributions of wavelength and texton diameter, we averaged the relative smoothness of each reference surface in Experiment 4 and plotted the resulting mean judgments as functions of both parameters in Figure 2.11. The resulting curves show common effects of texton diameter regardless of the texture wavelength. The data show that smoothness is influenced by both the size and spacing of textons such that increases in the surface area contacting the skin are perceived as relatively smoother, regardless of whether this results from enlarging individual textons, increasing their proximity or combinations of these properties. The smoothest textures we tested are those with the shortest wavelengths and the largest diameter textons ( $\lambda$ =0.75 mm, d = 0.5 mm); the ratio of texton diameter to wavelength = 0.667. The least smooth (i.e., roughest) texture had small diameter, widely spaced textons ( $\lambda$ = 1.25 mm, d = 0.1 mm); so  $d/\lambda = 0.08$ . The combination in the middle ( $\lambda$ =1.0 mm, d = 0.3 mm) is judged smoothest on only 50% of trials.



Figure 2.12: Judgments of relative smoothness of textures correlate with differences in texton contact area (equivalent to texton density) on the skin; both are linked to both texton diameter and texture wavelength. Data is re-plotted from Figure 2.4. Although the individual data points are derived from pairs of textures of different wavelengths, subjective perceptions of relative smoothness appear to be independent of the specific wavelengths tested, but only upon the relative areas of contact and blank spaces on the fingertips.

### 2.3.5 How do subjects judge surface smoothness?

When subjects discriminate the relative smoothness of textures that differ in wavelength, what are they actually detecting? One possibility is that they are measuring the relative mean spacing between pairs of textons as they move their fingers across the surfaces. In isotropic textures, the textons are unevenly spaced around the mean wavelength value. However, subjects perceived anisotropic textures as only slightly different, and only at wavelengths of 1.0 or higher.

Another possibility is that subjects compare the density of textons contacting the fingertip skin as they scan the pair of surfaces simultaneously. Texton density may be easier to detect as entire surfaces are evaluated rather than a random set of points. For example, a 0.875 mm comparison texture is distinguished as smoother than an 0.75 mm reference texture on 82% of trials (Fig. 4); the mean wavelengths of this pair differ by 0.125 mm, but the



Figure 2.13: Judgments of relative smoothness of textures depend upon differences in texton contact area (A) and density (B) on the skin, which in turn are linked to both texton diameter and texture wavelength. Data re-plotted from Figures 2.4, 2.8 and 2.9. Although the individual data points are derived from pairs of textures of different wavelengths, subjective perceptions of relative smoothness appear to depend upon differences in both wavelength and texton size, which in turn modify the total contact area on the skin rather than the density of contact points on the fingertips.

 $\lambda$ =0.75 mm texture contains 178 textons/cm2, while the  $\lambda$ = 0.875 mm texture contains only 131 textons/cm2. A further possibility is that subjects compare the total skin area contacted and indented by the two textures. Skin contact area clearly depends upon the total density of textons per square centimeter of skin and the diameter of each texton. Note that the contact area is equal for the isotropic and anisotropic surfaces of the same mean wavelength. When analyzed graphically (Figure 2.12, left), judgments of smoothness based on estimates of skin contact area yield similar curves are superimposed for all of the three reference wavelengths. Nearly identical results are obtained when comparing texton density (the number of textons/cm<sup>2</sup>) (2.12, right) suggesting that the underlying neural mechanisms used on individual trials engage the entire surface palpated during motion.

In Figure 2.13 we show that large-diameter textons with closer spacing produce greater sensations of smoothness. The proximity of surface elevations prevents deformation of the skin and displacement of papillary ridges into the interstices between textons.

## 2.4 Discussion and Conclusions

In this study, we used 3D printing to create textured surfaces with controlled texton size, spacing and arrangement. The surface textons had mean wavelength of 0.6-1.4 mm and were shaped as flat or rounded truncated cones with diameter 0.1-0.5; they were distributed in either anisotropic or isotropic arrangements. These surfaces allowed us to independently assess the effect of texton spacing and size on human percepts of surface smoothness. Results of two-alternative forced choice protocols indicate that both wavelength and texton dimensions influence human judgments of relative smoothness: the smoothest textures were composed of textons with small wavelengths and large diameters, while the least smooth textures comprised large wavelengths and small-diameter textons. We also found that textons arranged in regular, anisotropic patterns are judged slightly smoother than isotropic textures with textons jittered

with the same mean wavelength. We concluded that percepts of texture are related not only to the distance between individual pairs of textons, but rather to the overall skin contact area and spatial distribution integrated by the palpating fingertip.

# 2.4.1 3D printing technology yields better control of texture surface properties

Our stimuli offer an improvement to the traditional surfaces used in tactile perception of roughness. In the past, many studies have used existing textured surfaces like sandpapers (Hollins and Risner (2000); Bilaloglu et al. (2015)), which are not well-suited for perceptual studies, as they are not homogeneous and vary in unpredictable ways across manufacturers and samples. Artificially produced stimuli for tactile studies are typically either square gratings manufactured using machine engraving (Lederman and Taylor (1972); Sathian et al. (1989); Sinclair and Burton (1991); Yoshioka et al. (2001)) or raised dot stimuli (Blake et al. (1997a); Blake et al. (1997b) Connor et al. (1990); Dépeault et al. (2009); Hollins and Bensmaïa (2007); Meftah et al. (2000); Phillips et al. (1990); Phillips et al. (1992)). The latter provides the more natural and variable textured surface, but the manufacturing process, typically using photo-embossing, has limited usability. Photo-embossing allows only a single raised height, typically less than 1 mm, in a flexible plastic material. In contrast, the stereolithography printing technology that we use solidifies rigid objects in individual thin layers with a resolution of 0.05 mm, which allows complete control over geometry with high accuracy. Our raised dot stimuli have smaller texture elements and closer texton spacing than those used in previous studies.

## 2.4.2 Papillary ridges as tactile processing units for textures

All of the textures used in this study had spacing larger than the experimentally derived papillary ridge spacing of 0.4 mm. Thus, neighboring textons in our basis set of textures (isotropic with 0.3 mm diameter textons and wavelengths of 0.75, 1.0, and 1.25 mm) typically stimulated mechanoreceptors in different papillary ridges. Our data suggest that the papillary ridge might serve as the basic computational unit of glabrous skin. Merkel cells are located in clusters at the base of the dermal ridges; each Merkel cell is innervated by a single axon with multiple branches that innervate several Merkel cells. Each cluster of Merkel cells in glabrous skin is innervated by several afferent fibers (Type SA1), yielding substantial overlap of receptive fields. Meissner corpuscles are located in dermal papillae along both sides of the epidermal ridges (Cauna (1956); Paré et al. (2002)). They are innervated by RA1 fibers that may branch as many as 18 times to multiple Meissner corpuscles; conversely, each Meissner corpuscle is innervated by 2-5 axons, giving rise to overlapping receptive fields of individual afferents (Paré et al. (2002); Nolano et al. (2003)). Each papillary ridge is innervated by unique combinations of sensory afferents, and the ridges in each finger are fairly uniform in width, thereby providing an anatomical grid structure for localizing tactile stimuli on the fingertips.

### 2.4.3 Models of neural representation of textures

In previous studies, Hollins and Risner (2000) proposed a duplex theory of perceived roughness as two separate qualities: large-scale roughness of large (> 0.2 mm) features detected spatially without hand motion, and small-scale roughness eliciting vibrational cues during hand motion over surfaces. Large-scale roughness is mediated primarily by Merkel cell afferents responding to static pressure (slowly-adapting Type SA1 fibers) which have small receptive fields (Phillips and Johnson (1981); Johansson and Vallbo (1979); Connor et al. (1990), Connor and Johnson (1992), Phillips et al. (1990); Phillips et al. (1992); Vega-Bermudez and Johnson (1999)). Smaller features are perceived primarily during dynamic touch by rapidly-adapting motion sensors (Type RA1 and RA2 afferents) that innervate Meissner and Pacinian corpuscles respectively (Bensmaïa and Hollins (2003); Hollins and Bensmaïa (2007), Weber et al. (2013), Manfredi et al. (2014)).

Another theory of texture, called the spatial variation hypothesis (Connor et al. (1990); Connor and Johnson (1992), Blake et al. (1997a); Yoshioka et al. (2001)), posits that periodic variations of bursts and silences in the population of SA1 fibers provide a dynamic, isomorphic image of the texture pattern as it is scanned over the skin. Yoshioka et al. (2001) posit that the firing rates of SA1 fibers fluctuate periodically in phase with the passage of individual textons across their receptive fields, and differences in mean firing rates between neighboring SA1 receptive fields yield a spatial derivative that accounts for perceived roughness.

This theory is based on two hypotheses: (1) The receptive fields of SA1 fibers have a common geometry, with a highly sensitive center point and graded sensitivity in the periphery and (2) roughness perception requires an isomorphic representation the contacted surface. Unfortunately, these postulates are unproven and likely oversimplified. Simple graded sensitivity profiles of receptive fields on the fingertips do not match experimental data: for example, Vega-Bermudez and Johnson (1999) used arrays of small punctate probes to measure sensitivity within SA1 and RA1 receptive fields; their data showed elongated, asymmetric receptive fields that differed in size and sensitivity. Moreover, when pairs or groups of probes were presented on the skin, they elicited mutual attenuation of spike trains at distances up to 3 mm, suggesting that responses to textures cannot simply be predicted by the activity generated by an individual probe itself (Vega-Bermudez and Johnson (1999)).

Studies of the dimensions of tactile receptive fields in the human hand by Johansson and Vallbo (1979) indicate that the receptive fields of SA1 afferents span 5-10 papillary ridges, and have multiple points of high sensitivity. He suggested that the punctate sensitivity in these receptive fields reflects the separate activation of different mechanoreceptors on the same afferent fiber, a feature that has been demonstrated anatomically for Merkel cell afferents in both glabrous and hairy skin (Iggo and Muir (1969); Paré et al. (2002); Nolano et al. (2003); Lesniak et al. (2014). Recent studies by Pruszynski and Johansson (2014) show complex interactions within cutaneous receptive fields in which the multiple points of sensitivity interact to yield signals of edge orientation or surface curvature, suggesting that the complex structure of cutaneous receptive fields can implement feature detection in a manner similar to the diverse properties of retinal ganglion cells demonstrated in a variety of recent studies (Sanes and Masland (2015)).

#### 2.4.4 Neural ensembles encode the spatial properties of textures

While Meissner corpuscle, Merkel cell and Pacinian afferents respond to textured surfaces scanned over their receptive fields, SA1 fibers are considered the principal class responsible for sensations of roughness and smoothness, because their firing patterns directly mirror the pattern of textons and therefore provide an isomorphic image of the stimulus (Connor et al. (1990); Connor and Johnson (1992); Phillips et al. (1990); Phillips et al. (1992); Blake et al. (1997a); Blake et al. (1997b); Yoshioka et al. (2001), Yoshioka et al. (2007)). However, we found that different combinations of texture wavelength and texton dimensions yielded equivalent percepts of smoothness, suggesting that isomorphism is not a necessary component of smoothness perception. We propose that all three types of sensory inputs are important for giving rise to sensations of surface irregularity. While a strong argument can be made for the role of SA1 afferents in static texture percepts, it is well-known that hand motion across textures enhances the percept of an irregular surface. Perhaps the lower-fidelity inputs from RA1 and RA2 fibers enhance sensations of surface irregularity through skin vibration or motion of the papillary ridges. Rather than considering textures as simple representations of individual textons, we propose that hand motion across textured surfaces activates unique ensembles of afferents that fire together as the fingers traverse the surface. In regular, anisotropic surfaces, the textons contact the same groups of afferents repeatedly, so that each afferent fires concurrently with a set of equally-spaced fibers according to the texture wavelength, regardless of the speed of motion. Different wavelengths activate different partners in the ensemble. Isotropic textures stimulate different groups of afferents because the textons are scattered in a random fashion on the surface, and so each afferent couples with different touch receptors during the passage of the finger over the texture. The alteration in partners may explain why the isotropic surfaces feel less smooth than the anisotropic regular arrays: anisotropic textures stimulate the same groupings of afferent fibers at the same time in a regular pattern, and the brain may integrate this consistent pattern of active and silent afferents as smooth; isotropic textures are random and therefore not predetermined in this way.

# Chapter 3

# A Quantitative Perceptual Model for Tactile Roughness

We address the problem of mapping a surface texture's geometry to its tactile roughness. This chapter is based on the publication Tymms et al. (2018) in collaboration with Esther P. Gardner and Denis Zorin. All work presented in this chapter is entirely my own.



Figure 3.1: Given an input surface geometry, our model computes the tactile roughness by computing skin deformation using elasticity simulations and sampling the resulting compressive strain field. Our model enables the fabrication of tactile objects with specified roughnesses.

## 3.1 Introduction

Tactile perception consists of four "coordinates": roughness, compliance, stickiness, and thermal sensitivity. Of these, surface roughness is known to be the most significant for judging a material (Tiest (2010)).

Varying surface roughness is common in conventional technologies, such as injection molding for plastic, and, in a more restricted form, in *knurling* in CNC machining. Additive fabrication technologies drastically increase the flexibility of roughness control; on the other hand, as the range of materials used by current additive technologies is more limited, roughness and other tactile properties often must be controlled with geometry variation, rather than with the choice of material.

The relationship between surface geometry, material properties and tactile perception is intricate, which makes the task of producing and designing tactile properties difficult. For many aspects of visual and auditory perception, a variety of models (e.g., perceptual color models and equal-loudness curves) are available, and these are broadly used for applications such as rendering and sound processing and synthesis. Our level of understanding of tactile perception is far less mature. Although many studies have been done over time, a widely accepted model is still absent: progress has been slow due to the complexity of the tactile system and the difficulty of producing controlled stimuli. An important goal would be to develop a model of tactile sensation that can be used for tactile "rendering," i.e., producing objects with controlled tactile feel. Important steps in this direction were made recently in the context of additive fabrication applications by Piovarči et al. (2016), who developed a model for compliance perception that can be used to control one dimension of tactile perception of 3D printed objects.

In this chapter, we focus on another dimension of tactile perception: roughness. Digital fabrication makes it more practical to control roughness directly and at the same time provides

a way to study perception of roughness by producing diverse fine-scale stimuli for studies.

Tactile roughness is perceived as the uneven pressure on the skin when a surface is touched or as temporal vibrations when the skin moves over a surface (Tiest (2010)). Human skin contains four different types of mechanoreceptors that mediate tactile sensation of spatial distributions, vibration, and skin stretch, and this low-level processing is followed by higher-level processing. Nevertheless, it is generally accepted (Hollins and Risner (2000)) that roughness sensation is well-described by at most two dimensions, one of which can be described as roughness proper (large-scale roughness), and the other as vibrational roughness corresponding to very small-scale effects.

In this chapter, we propose a computational model relating surface geometry to perceived (large-scale) roughness based on strain fluctuation variation in an elasticity model. We use human perception studies to compute a perceptual space of roughness by applying multidimensional scaling, and we demonstrate that our model matches experimental results significantly better than previously proposed models. We show how this model can be applied in the context 3D printing to achieve a range of effects.

As a part of our experiment design, we developed an approach to producing a range of controlled tactile stimuli, which is likely to be of value for future studies of roughness. The 3D stimuli models, the code for geometry generation and the raw data of the experiments will be released to encourage further exploration of this topic.

## 3.2 Related Work

Our work builds on sources in several areas, including psychophysical literature and work in computer graphics related to perceptually-based rendering and digital fabrication.

## 3.2.1 Tactile fabrication

Recently, several works have explored the fabrication of objects with tactile properties. Our work is closest to Piovarči et al. (2016) in aims and in the methods we use to construct and evaluate our model. This work develops a model for perceptual *compliance* using stimuli fabricated from materials with different compliance properties. In our work, we use similar experimental protocols and multidimensional scaling analysis techniques to find a perceptual space, but we develop a model for roughness. Compared to compliance, roughness is primarily related to small-scale surface geometry instead of overall bulk material properties; therefore, a much larger physical space of possible surface profiles is mapped to a single perceptual dimension.

Another work with similar aims is Elkharraz et al. (2014), which fabricated texture plates from a set of *visual* textures converted to shallow height maps, asked human subjects to rate the resulting textures according to a set of adjectives (including "rough"), and analyzed a set of computational texture features to find those highly correlated with the perceptual scales. Although this chapter reports success with prediction of tactile roughness, the data set is quite limited compared to the dimension of the feature space. In Section 3.5, we compare this model to ours and demonstrate a significant improvement in performance.

Other recent work in the fabrication domain has aimed to facilitate the incorporation of tactile properties in 3D printed models. Torres et al. (2015) provides an interface to fabricate objects with a user-specified weight, compliant infill, and rough displacement map. However, their roughness metric relies on texture feature size, which is not always definable and does not describe a comprehensive model for all textures. Chen et al. (2013) also develops methods to fabricate objects with specified deformation behavior and textured surface displacement, but it similarly does extend to tactual perceptual specifications. Our model offers an improvement to surface roughness specification in these types of interfaces. Relatedly, Lau et al. (2016)



Figure 3.2: Diagram of the structure of human skin (CNX (2017)). Roughness perception is primarily mediated by Merkel cells, or SA1 receptors, located approximately 0.75 mm deep in the skin.

has developed a method to analyze meshes for tactile saliency, identifying mesh regions most likely to be touched. Incorporating tactile saliency with our work could create a natural tool to suggest the application of appropriate textures on salient regions of objects prior to fabrication.

### 3.2.2 Psychophysics of roughness perception

**Perception** Research in the sense of touch, while extensive, is still limited when compared to vision and hearing. Various works have aimed to quantify different aspects of the sense of touch. Research suggests that tactile perception falls in a multidimensional space varying along 3 (Hollins et al. (1993)) or 4-5 (Tiest (2010)) dimensions; of these, roughness has been found as the most significant dimension. Roughness can further be divided into two aspects: small-scale roughness caused by features less than 0.1mm in size, which elicit vibrational cues perceived by Pacinian corpuscles deep in the skin; and large-scale roughness, which is mediated primarily by Merkel cells at the base of the epidermis that respond to strain (a third mechanoreceptor, the Meissner's corpuscle, also plays a part in lower-frequency vibration

detection). The remaining three dimensions are compliance, stickiness, and surface warmth or heat conductivity.

A major issue that has prevented the comprehensive study of tactile perception, and specifically roughness perception, is the lack of suitable stimuli: in comparison to the generation of visual or auditory stimuli, tactile stimuli are relatively difficult to manufacture with the desired accuracy. Most early studies in tactile perception used different types of common manufactured surfaces, such as sandpapers (Hollins and Risner (2000)), paper and fabric (Chen et al. (2009);Manfredi et al. (2014);Weber et al. (2013)), and other everyday items. However, these surfaces are not ideal as stimuli because they vary across multiple dimensions, and their surface features cannot be easily quantified; even graded sandpapers vary widely by manufacturer.

To overcome these problems, some studies in roughness perception have manufactured artificial stimuli. The two common types of custom stimuli are square gratings, which are manufactured using machine engraving (Lederman (1974);Yoshioka et al. (2001)), and photoembossed dots. The studies suggest that perceptual roughness has a positive correlation with groove width or spacing and a slightly negative correlation with ridge or dot width. Yoshioka et al. (2001) and Connor et al. (1990) developed neural models using these stimuli; they found that the mechanoreceptor firing rates elicited by touching these surfaces were correlated to perceived roughness via firing rate *spatial variation*. The spatial variation hypothesis was also explored recently by Goodman and Bensmaia (2017), who showed that it could predict perceptual roughness for several raised-dot stimuli used in past experiments. We use this hypothesis as a base for our model in Section 3.5.

The artificial stimuli used in these past experiments have significant limitations. While engraved gratings are precise, they present a limited and unnatural stimulus. The photoembossing process most often used for dot stimuli also has several limitations; it effectively supports only two levels of height (unblocked areas are solidified, and blocked areas are not) with little control over the intermediate areas, and the material is quite flexible. In contrast, recent developments in fabrication, such as the stereolithography 3D printing we use to manufacture our stimuli, allow the creation of solid stimuli with any surface geometry at a high resolution, covering the complete range for (large-scale) roughness. In fact, to our knowledge, no psychophysics study to date has used stimuli with raised dots as small or finely spaced as those used here. Additionally, no study to our knowledge has tested the roughness of textured curved surfaces.

**Physical modeling** Research in perception has also worked to model the lower-level mechanoreceptor responses in humans and related primates. Several works have aimed to model the skin mechanics and receptor responses: Phillips and Johnson (1981) created a continuum mechanics model for the skin contacting bars and gratings, and Dandekar et al. (2003) developed a 3D FEM model to accurately match skin displacement under line loads and predict Merkel cell responses to these indentations. Both studies found that Merkel cells have a firing rate closely matched to the maximum compressive strain elicited in the skin. Indeed, recent strides in molecular biology (Woo et al. (2014)) have shown that Merkel cells express the mechanically-activated ion channel Piezo2 as a means to mediate mechanosensation. This relation between strain and firing rates is used as a basis for our computational model in Section 3.5.

## 3.2.3 Haptic rendering

Other work exploring tactile perception has been motivated by haptic applications. Early haptics research focused on virtual touch using rigid styluses or probes as feedback devices. For example, Otaduy et al. (2005) developed a perceptual model for haptic rendering of forces and vibrations elicited by the contact of textures in this manner. Several studies have measured perceived surface roughness of virtual textures using a stylus, e.g. Klatzky and Lederman (1999), Yoshioka et al. (2007), Okamoto et al. (2012). Importantly, these works are based upon a vibratory perceptual model of texture and roughness perception, as transmitted through a rigid object. In contrast, we aim to manufacture objects to be touched with bare skin, which provides more natural and improved tactile information.

Other recent developments have enabled the rendering of tactile features on various types of touch displays. Many types of tactile touch-screens have been proposed, e.g., Kim et al. (2013) and Meyer et al. (2013), which use electrostatic attraction to alter friction and simulate texture or gradient. Bau and Poupyrev (2012) develops AR technology using reverse electrovibration, which injects electric signals into the user to elicit smaller-scale tactile sensations. However, this is still fundamentally vibratory signaling. Iwata et al. (2001) developed an early method of rendering haptic height surfaces directly by projecting an image on a flexible screen over an actuator array. More recently, Hashizume et al. (2016) developed a tactile rendering display using magnetorheological fluid (MRF), a liquid that changes viscosity in response to magnetic fields. These methods represent promising advancements to on-the-fly rendering of real textures, and could be used in conjunction with our model to further explore roughness perception and texture rendering.

## **3.3** Overview and Main Results

The main goal of this work is to develop a computational model describing the perceptual roughness of a given geometric surface texture, which can be applied to produce a range of tactile surface behaviors.

**Model summary.** Given an input 2D height field describing a surface texture H(x, y), our model is a function f(H) producing a scalar value estimating the perceptual roughness of the texture. Our pipeline is depicted in Figure 4.1. The perceptual roughness estimate f(H)

is obtained by first running a simulation to find the contact area and resulting deformation of a skin-like elastic medium in contact with the surface texture. Then the field of maximum compressive strain is computed at a fixed depth corresponding to the average depth of Merkel receptors. The strain field is sampled at pairs of points separated by a fixed distance, extracted from experimental data, to find the *mean strain fluctuation variation*, defined as the mean absolute difference between strain magnitudes of the sampled pairs. This value describes the perceptual roughness of the input geometry.

We use psychophysical experiments to validate that the perceptual space of roughness can be described by a single dimension and to construct a metric on this space. We demonstrate that our model describes this space with a linear relationship (r = 0.911). Experiments are also used to place a standard scale of reference textures in the perceptual space, which can be used as a reference set to match against other textures to predict roughness equivalence.

Our model tuning and validation process consists of the following steps:

- We synthesize a set of textures comprising a variety of parametric and natural textures. We fabricate these textures as flat plates using a high-resolution (30  $\mu m$ ) stereolithography 3D printer.
- We perform a series of psychophysical experiments with human subjects, comparing the differences between textures.
- We use non-metric multidimensional scaling (NMDS) with the experimental results to establish that the roughness perceptual space is one-dimensional (Section 3.4) and to place the stimuli in this space.
- We acquire the actual geometry of the printed plates using micro-CT scanning.
- For each texture, we perform FEM simulation to compute the deformation of a skin-like elastic medium when pressed in contact with the texture. An iterative process is used

to resolve the contact area.

- From the simulation, we compute the maximum compressive strain field at a depth of 0.75 mm, and we compute f(H) as the strain fluctuation variation of this field.
- We test the linear dependence between the coordinates assigned by the NMDS to the stimuli  $H_i$  and the roughness estimates  $f(H_i)$  produced by our model, and tune the sampling parameters of the model to match the perceptual data as closely as possible (Section 3.5).

## 3.4 Perceptual Space

In this section, we describe how we establish that the *perceptual space* for (coarse) roughness is one-dimensional and construct a map from stimuli to points in this space. The overall idea, following from previous work, is to use experiments to obtain an estimate of relative perceptual proximity for triplets of stimuli (i.e., which of a pair of stimuli feels closer to a reference stimulus). A multi-dimensional scaling algorithm is then used to assign *n*-dimensional points to stimuli so that Euclidean distances between these points have the same ordering as obtained from the experiments: stimuli corresponding to closer points feel more similar than stimuli corresponding to points at a larger distance.

## 3.4.1 Stimuli

A fundamental issue in the study of perceptual roughness is the large variety of possible surface textures. Inherently, conducting experiments with human subjects limits the number of textures we can study: using three-way comparison experiments, with N textures we need to obtain a reasonably large sample of  $\binom{N}{3}$  combinations. We used 46 textures in our experiments. We used two distinct type of textures as stimuli: artificially synthesized textures, and real-life "natural" textures described below.

**Synthetic texture geometry** Synthetic textures serve two purposes: (1) to provide a one-dimensional family that can be used as a reference scale for roughness, and (2) to explore the effects of some of the geometry parameters that previous studies have shown to be important for tactile perception.

Specifically, we choose bump textures which allow us full control over texton spacing, shape, and distribution (in the present study, all textures had elements with random isotropic distribution). Bump spacing allows control of the spatial frequency of contact points between the texture and the skin, which is known to be correlated with roughness; bump shape, on the other hand, controls the size of the contact zones and the sharpness of the transition between contact and non-contact zones, which has a significant effect on strain distribution, a key component of our model. Unlike, e.g., ridge patterns, our bump textures are isotropic, so we can factor out the aspect of strong regularity.

The 3D modeling procedure used to specify isotropic textures is shown in Figure 3.3. We begin with a magnitude spectrum, representing the magnitude component of the Fourier transform of the image. For random, isotropic textures, with one dominant wavelength over all directions, this magnitude spectrum is visualized as the outline of a circle with a radius given by  $s/\lambda$ , where s is the pixel size of the image and  $\lambda$  is the dominant wavelength (Figure 3.3a).

We then take the 2D inverse Fourier transform using the magnitude and a random phase matrix, resulting in a random texture with a dominant wavelength of  $\lambda$  (Figure 3.3b). To produce the bump texture, we take the relative maxima of the inverse Fourier transform to obtain a dot pattern yielding the centers of the bumps. The resulting textured surface has textons arranged with an average spacing at the specified wavelength (Figure 3.3c,d). In



Figure 3.3: Modeling process for isotropic textures. The modeling process allows for variation of texton arrangement, spacing  $\lambda$ , and shape (here we control the tip diameter d).

this way, we have complete control over the local bump shape: in our experiments we use truncated cones with or without a rounded cap.

We fabricated a reference set of 13 standard isotropic bump samples varying in a single parameter, average distance between bumps, which ranges from 0.625 to 1.625 mm. These textures have standard texture elements shaped as 1mm tall truncated cones with spherical caps 0.3mm in diameter. Additionally, we fabricated 5 isotropic bump samples with texture elements shaped as truncated cones with flat tops of varying diameters from 0.1 to 0.5 mm, to explore the dependence on the contact area.

We also fabricated a set of 28 real-world texture heightmaps; of these, 24 were acquired from high-resolution scans on the SurfaceMimic 3D scan repository and three from the Brodatz texture database, and one was procedural. The texture set was composed of many common natural and manufactured materials, such as burlap, leather, and stucco; textures varied in height, pattern, and isotropy. We fabricated these textures out of the same material, instead of, e.g., using the natural samples, to eliminate the effects of small-scale roughness and compliance.

All texture samples were fabricated as 25 by 25 mm square plates using a B9Creator stereolithography 3D printer with 50  $\mu m$  resolution in xy and 30  $\mu m$  resolution in z. Textures ranged from having little surface texture to having greatly varying surface texture. A selection of stimuli is shown in Figure 3.7, and a table of all 46 textures is provided as supplementary material.

**Threshold of discrimination** To select the reference set of bump textures, we refer to data gathered in our earlier study (described in detail in Tymms et al. (2017); all other studies presented in this chapter have not been described elsewhere).

In this previous experiment, 16 subjects participated in two-alternative choice trials to identify which of two presented bump textures felt smoother. To this data, we fit psychometric curves (Figure 3.4) and extracted the absolute thresholds  $\sigma$ . The Weber fraction, or relative threshold of discrimination, describes the proportional difference in texture wavelength required in order to distinguish (with 75% accuracy) between two textures. The Weber fraction was found to be 0.19, which is in good agreement with the existing literature (Figure 3.5).

This value serves two important purposes: first, to act as a threshold for selecting substantially different textures; and second, to demonstrate that our choices for reference textures sample the perceptual space densely enough. At the smoother end of the scale, we fabricated textures with 0.0625mm wavelength differences; at the rougher end we used an interval of 0.125mm. These reference textures are shown in Figure 3.6 along with the threshold  $\sigma$ . In most cases our textures sampled the space with a density around  $2\sigma$ .

## 3.4.2 Experiments

Our experiments serve three purposes in this study.



Figure 3.4: Psychometric curves fit to percentage data, from our previous study. Errors bars show SEM across subjects.



Figure 3.5: The threshold of discrimination is proportional to the tested wavelength by a factor of 0.19, known as the Weber fraction.



Figure 3.6: The standard scale of reference textures (numbers 1 through 13) depicted along a logarithmic line scaled to the threshold of discrimination  $\sigma$ . The textures sample the perceptual space at a greater density than the threshold of discrimination.



Figure 3.7: Seven examples of the 46 textures used in our experiments. Three bump textures are shown with a green background, and four natural textures are shown with a blue background. From left to right: standard bump texture with wavelength 0.625mm; standard bump texture with wavelength 1.625mm; flat bump texture with wavelength 1.0 and size 0.4 mm; foam; lizard skin; stucco; knit wool. A list of all 46 textures is provided in the supplementary material.

- We validate the hypothesis that perceptual roughness is reasonably measured by a one-dimensional parameter; more specifically, that any set of textures can be ordered in a way so that if one texture comes before the other, it is always perceived as rougher.
- We show that the perceptual roughness ranking inferred from the experiments is closely matched to the one given by our choice of the model for roughness perception, the strain fluctuation variation model.
- By including a one-parametric reference set of textures in the set of stimuli, we establish a correspondence between a simple parameter of the family (spacing of the bumps) and the physical roughness measure.

The two most common types of psychophysical experiments used with human subjects involve either pairwise comparisons of roughness of stimuli (which stimulus feels rougher) or estimating subjective roughness on a scale, e.g., 0-10. The former provides a simpler and more intuitive task for the subjects, and as such the data is more reliable. However, the results are harder to use for perceptual space dimension analysis, as they do not provide direct information on the perceived distances between stimuli. The second type of experiments is more suitable for dimension analysis, but the task is more complex and leads to less reliable results.



Figure 3.8: In a trial, participants were presented with three texture samples. They touched each texture using the index finger and answered whether the leftmost or rightmost sample felt more similar in roughness to the middle sample.

In line with Piovarči et al. (2016), we use a variation of the first type of the experiment, where instead of a single pairwise comparison between two textures per trial, two test textures are compared in their perceptual proximity to a third, reference texture. This type of experiment, as we explain below, can be used with multidimensional scaling to determine the perceptual space and dimensionality *without* relying on subjects assigning a subjective rating to each stimulus.

The experiment setup is shown in Figure 3.8. During each trial, the subject was given three textures, arranged in a row in a fitted case. They were asked to feel each texture by pressing with the index finger and to answer whether the leftmost or rightmost texture felt more similar in roughness to the center texture. Subjects were free to feel each texture multiple times before making the decision. Subjects initiated a trial by pressing down the right and left arrow keys on a provided keyboard with their non-dominant hand before making contact with the textures with the dominant hand. They indicated their choice (the leftmost or rightmost texture) by releasing the left or right arrow key, respectively. This method allowed us to record both the subjects' responses and the amount of time taken for each response.

We included a set of practice trials at the beginning of each session to familiarize the subjects with the mechanics of the task and to ensure that they understood the task protocol.



Figure 3.9: The placement of our 46 texture samples in one dimension using the NMDS algorithm. The number labels correspond to those in Figure 3.7 and in the table in the supplementary material.

Visual feedback was avoided by using a cut box placed over the texture case so that textures could be touched but not seen from the subjects' viewpoint. Fourteen subjects (21-35 years old) participated in these experiments. All self-identified as strongly right-handed and reported normal sensory and motor functionality of the hands and fingers. Each subject performed trials for 1-2 hours, resulting in between 100 and 250 triplet comparisons. The order of trial comparisons was randomized.

#### 3.4.3 Data analysis

**MDS** We briefly review non-metric multidimensional scaling (NMDS), which we use to find a Euclidean embedding of the roughness space of our samples.

This method takes as input a set of triples  $\{(i, j, k)\}$  where i, j, k are stimuli used in a trial (with j as the reference sample), and the ordering  $D_{ij} < D_{jk}$ , where  $D_{ij}$  is the perceptual distance between samples i and j. In other words, the input consists of the ordering of the pair comparisons, without magnitudes of the dissimilarities.

As in classical MDS, the problem is transformed into one that can be stated in terms of the Gram matrix K. Because all distances are assumed to be nonnegative, the set can be transformed to

$$S = \left\{ (i, j, k) | D_{ij}^2 < D_{jk}^2 \right\}.$$
Now

$$D_{ij}^{2} = \|x_{i} - x_{j}\|_{2}^{2} = x_{i}^{\top} x_{i} - 2x_{i}^{\top} x_{j} + x_{j}^{\top} x_{j}$$
$$= K_{ii} - 2K_{ij} + K_{jj}.$$

Therefore we can write the triplet conditions as

$$= K_{ii} - 2K_{ij} + K_{jj} < K_{jj} - 2K_{jk} + K_{kk}.$$

Thus the goal is to find a Gram matrix K that satisfies the inequality constraints of this form for every triplet (i, j, k) in S. Since it is a Gramian matrix, K is the inner product for some set of points.

The set of constraints does not define a unique matrix K: it is still subject to scale, translation, and rotation. Therefore we simply constrain K so that it is centered at the origin and has a range of (-1,1).

Finally, we want to minimize the dimensionality or rank of K while also ensuring that it adequately satisfies the inequality constraints. As the rank of a matrix is a non-convex term and minimizing it while optimizing for inequality constraints is an NP-hard problem, Wills et al. (2009) formulates the problem as instead minimizing the trace of the matrix. The full problem is formulated as:

$$\arg\min_{K,\xi} \sum_{(i,j,k)\in S} \xi_{ijk} + \lambda \operatorname{Tr}(K)$$
$$\forall (i,j,k) \in SK_{kk} - K_{ii} + 2K_{ij} - 2K_{jk} \ge 1 - \xi_{ijk},$$
$$\xi_{ijk} \ge 0, \sum_{ab} K_{ab} = 0, K \succeq 0.$$

 $\xi_{ijk}$  are slack variables introduced to allow for violations in the inequalities, and the variable  $\lambda$  is a regularization parameter which balances the complexity (i.e. dimensionality)



Figure 3.10: Left: cross-validation determines the optimal  $\lambda$  value as 0.7. Right: most of the variance is confined to the first dimension, indicating a good fit in one-dimensional space.

of the model with the fit. The SeDuMi solver for Matlab is used to solve this optimization problem.

**Cross-validation** The goal of cross-validation is to find the optimal  $\lambda$  value. We use 10-fold cross-validation as suggested in Wills et al. (2009). In each iteration, the data is divided into 10 sets, with one set treated as the testing set and the rest as the training set. The optimization is run on the training set for a given  $\lambda$ , and the average testing and training error is reported as the mean across these trials. We aim to optimize the tradeoff between testing and training error. When  $\lambda$  is small, the algorithm favors reducing the violations for all conditions and results in low training error but a high testing error, implying that the embedding does not generalize and may over-fit to noise in the data.

We obtained the optimal embedding with  $\lambda = 0.7$  as shown in Figure 3.10. The spread for this embedding shows the variance across each dimension; most of the variance is contained in the first coordinate, indicating that the space fits well in one dimension.

**Errors** To find margins of error, we use a standard bootstrapping technique. We recomputed the embedding 500 times by randomly resampling the data points with replacement, and we compute confidence intervals as the 5th and 95th percentile of the resulting embeddings. The final embedding with these error bars is shown in Figure 3.9. Samples are numbered

according to the labels in Figure 3.7. Note that because of the large number of stimuli, only a small proportion of possible combinations was tested; therefore, the error bars represent upper bounds for error and are likely larger than the subjects' actual margin of error.

#### 3.4.4 Curved Surfaces

Many natural applications for rough textured surfaces involve 3D objects with nonzero curvature, rather than flat objects. An obvious question is whether the perceived roughness of textured curved objects is the same as that for textured flat plates. To answer this question, we performed an additional psychophysical experiment comparing a new set of curved textures to the set of flat textured plates. The stimulus set was manufactured in the same way and consisted of twelve singly curved surfaces, textured with one of three bump texture wavelengths of different roughness (0.75 mm, 1.0 mm, 1.25 mm). Textures had one of four different curvatures: concave or convex, with radius of curvature 20 mm or 40 mm, as shown in Figure 3.11. Here we define a concave object as having a negative radius of curvature.



Figure 3.11: Our curvature experiments tested the roughness of textured curved surfaces with one of four curvatures (20 or 40 mm, concave or convex) against the standard set of bump texture plates. Curved surfaces were textured with the standard bump texture in one of three wavelengths.

In experiments, subjects were presented with one curved bump texture and one flat bump texture. They were instructed to touch the surfaces with the index finger as in the previous experiment, and they answered which of the two textures felt smoother. Subjects performed between two and six comparisons per pair. Data was aggregated over all subjects to find the proportion for each pair, and the proportions were used to find the Point of Subjective Equality for each curved texture, i.e., the *flat* texture wavelength judged as equivalent to each *curved* texture. Here, we assume that if one textured surface is judged smoother than another in 50% of trials, the two are equivalent in roughness.

Figure 3.12 shows the point of subjective equality of the four curved textures for each wavelength. The overlapping shaded areas, as measured by the double arrows, show the interval for 19% threshold of the given reference wavelength, which represents the threshold of equivalence for that wavelength. For all wavelengths, all of the points fall well within this threshold area, indicating that the curved textures feel equivalent to their corresponding flat textures. While some data points (e.g. wavelength 0.75mm, radius -20) appear a small distance from the base wavelength indicated by the dashed line, most are close; furthermore, no trend exists over all of the textures to suggest that curvature has a consistent effect on perceived roughness. The small and seemingly random differences likely result from variations caused by printing.

From these results, we posit that moderate curvature (with radius of curvature many times larger than the characteristic texture scale) does not have any significant effect on perceived roughness, and that the human tactile system integrates shape and texture independently. In regions of extreme curvature on the scale of texture itself, the separation may become unclear and curvature might have an effect on perceived roughness. Characterizing perception of roughness in these areas is more complicated, as it becomes much more dependent on the complex details of contact and highly dependent, e.g., on the exact finger location or orientation of the applied force. We propose a method of separating underlying smooth shape and texture in our model in Section 3.5, and we show that simulations match our experimental data in cases of moderate curvature.



Figure 3.12: The points of subjective equality for all curved textures are plotted, with color indicating texture wavelength; the 19% threshold interval for each wavelength is indicated by the corresponding shaded intervals measured by the double arrows. All of the points of subject equality fall within their corresponding interval, indicating that the curved textures are judged equivalent in roughness to the corresponding flat texture of the same wavelength.

# 3.5 Model for Roughness

#### 3.5.1 Biological basis

Our computational model for roughness is built on several previous works in neuroscience and engineering. It is derived from a combination of two parts: first, the relationship between the physics of skin deformation and neural responses; and second, the relationship between neural responses and high-level perceived roughness. The former connection has been studied on nonhuman primates with direct measuring of skin deformation and neuron firing rates. The latter was studied using firing rate data from nonhuman primates and perceived roughness ratings from human subjects using the same stimuli.

In the context of the first question, Phillips and Johnson (1981) created a continuum mechanics model for skin deformation and tested several models for predicting the SA1 firing rate data under bars and gratings; they found that firing rates were most closely correlated to maximum compressive strain and strain energy density in the skin. Dandekar et al. (2003) developed an FEM model of the skin and examined this model in relation to firing rate data under line loads, finding again that SA1 firing rates were well-predicted by the maximum compressive strain at the receptor depth in the skin.

Connor and Johnson (1992) and Yoshioka et al. (2001) examined the second question of the relationship between firing rates and perceptual roughness assessments, using as stimuli embossed dots or square wave gratings with different spacings. After examining several hypotheses, they both found that perceptual roughness best matched to the spatial variation in SA1 firing rates, meaning the average absolute difference between SA1 firing rates, at intervals of approximately 2mm. They also verified that Merkel receptors were the major predictors of surface roughness; other mechanoreceptors (RA and PC) did not have strong correlation with roughness judgments.

We combine observations from these studies to hypothesize that *strain fluctuation variation* at the depth of mechanoreceptors in skin is a physical quantity well correlated with subjective roughness perception. We define strain fluctuation variation as the mean absolute difference of maximum compressive strain fluctuation between pairs of sample points in the skin, after the effects of bulk shape are eliminated. The difficulty of using this quantity is estimating the strain of the skin when in contact with specific geometry, which we discuss now.

#### 3.5.2 Simulation

In general, accurate simulation of skin deformation is a difficult problem, primarily because of the complex nonlinear and inhomogeneous mechanical properties of biological tissues and potentially high variability of mechanical properties among subjects.

However, we observed that the specific quantity of interest, variation of strain, is relatively insensitive to these properties: e.g. increasing or decreasing Young's modulus of the material results in relatively small changes in the contact with the surface (Figure 3.18).

We first simulate the skin deformation when in contact with particular texture geometry

of the texture defined by a height field H(x, y).

To describe our computation of the roughness value f(H), we introduce the following notation:

- $\mathbf{u}_H(u, v, w)$  is the field of displacements obtained by solving an elastic contact problem between a model for skin and subcutaneous tissue and the heightfield H(x, y). (u, v, w) are the coordinates in the material domain representing the tissue, with w = 0corresponding to the lower surface.
- $\epsilon(\mathbf{u}) = \frac{1}{2}(\nabla \mathbf{u} + \nabla^T \mathbf{u})$  is the small-deformation approximation of the strain tensor.
- $\lambda_3(\epsilon)$  is the largest-magnitude negative eigenvalue of a symmetric tensor.
- V(f) is the variation functional described in detail in the next section.
- $w_0$  is the depth of the receptors, which we take to be 0.75 mm Dandekar et al. (2003).

Then our roughness estimate f(H) can be written as a composition

$$f(H) = V(\lambda_3(\epsilon(\mathbf{u}_H(\cdot, \cdot, w_0))))$$

The critical and most expensive step is the computation of  $\mathbf{u}_H$  for a given H. Although we use simple linear elasticity as a model, this function is *nonlinear* due to the need to resolve contact. This function also depends on the choice of the model for tissue and applied pressure.

Skin model and geometry data. To approximate the skin, we use a two-layer block model created with Tetgen Si (2015), adaptively refined with about 24,000 nodes, which represents  $1cm^2$  in surface area and 0.5cm in height. The lower half of the has a Young's modulus of 0.042 MPa, representing all tissue, and the upper half, representing the bone,

has a Young's modulus of 18000 MPa, i.e. essentially rigid Agache et al. (1980). The force used for this model was 10 N, which we found in pilot experiments where subjects touched textured surfaces placed on a force sensor. As seen in Figure 3.18, however, the model is relatively insensitive to small changes in force.

While this model is rather crude, given the level of noise in the experimental data, we found it be adequate. We did not fit the parameters of the simulation to the data, but this would certainly be possible once larger datasets with less variance are collected.

We used as input H(x, y) scanned height maps of the textures, rather than the original digital models from which the textures were printed, to take into account the effects of the printing process (inflation, rounding of edges which results in decreased strain, etc). We acquired high-resolution 3D scans of all of the textures using a Bruker Skyscan 1172 micro-CT scanner.

**Resolving contact.** To build an accurate simulation, we must find the contact between the skin and the rigid surface. For most surfaces, this problem is nontrivial, as the skin may or may not come into contact with various parts of the surface geometry depending on the heights, sizes, and distribution of features. Because of the complexity of the surface geometries, we were unable to obtain reliable results from commercial FEM software supporting contact mechanics. Instead, we have implemented our own accurate simulation software based on simple and robust algorithm, illustrated in Figure 3.13.

First, the undeformed geometry is positioned so that it touches the top points of the texture, i.e. a map  $p(u, v, w) \to R^3$  is defined, so that  $p_z(u, v, 0) = \max_{x,y} H(x, y)$ . The points in contact with the texture are included in the initial contact zone  $\Omega_c$ .

The vertices constrained by this boundary represent the parts of skin that touch the upper crests in the contacted texture. Then, an iterative process is run with two steps to build the correct boundary condition. The simulation is run for each step. First, we add to



Figure 3.13: a) The iterative process simulates the contact between the skin (blue) attached to a rigid bone (red) when the skin contacts a textured surface (gray). b) The simulation begins with an arbitrary contact area set using a threshold (constrained vertices are shown in green). The resulting boundary condition may be underconstrained, as many vertices fall below the contact area (shown in red). c) All vertices that fall beneath the boundary are constrained. However, some vertices (as shown in orange) may be over-constrained, or stretched. d) Over-constrained vertices are released from the boundary. After a number of iterations, the result converges to a stable contact boundary condition.

the fixed boundary set  $\Omega_c$  any vertices that fall below the texture height H(x, y). However, this process may overestimate the vertices in contact with the substrate. Thus a second step of the iterative process releases vertices for which the elastic forces are pointing away from the contact surface. This iterative process terminates after it converges or after a number of iterations to approximate the contact condition. We found that the process typically converges in three of these 2-step iterations.

The pseudocode below summarizes the algorithm more formally;  $\sigma$  denotes the stress and **n** the normal to the surface.

 $\Omega_C \leftarrow \{(u,v) | \mathbf{p}_z(u,v,0) = H(\mathbf{p}_x(u,v,0), \mathbf{p}_y(u,v,0)) \}$ 

#### repeat

Solve for **u** with  $\Omega_c$  fixed

 $\mathbf{p}' \gets \mathbf{p} + \mathbf{u}$ 



(a) Texture 10 input sur(b) Texture 10 output face. strain.



(c) Texture 23 input sur(d) Texture 23 output face. strain.

Figure 3.14: Examples of simulation input heightmaps (left) and output compressive strain fields (right), visualized as grayscale height maps.

$$\begin{split} \Omega_c^{incl} &\leftarrow \{(u,v) | \mathbf{p}_z'(u,v,0) < H(\mathbf{p}_x'(u,v,0), \mathbf{p}_y'(u,v,0)), (u,v) \notin \Omega_c \} \\ \Omega_c^{excl} &\leftarrow \{(u,v) | \mathbf{n}^T \sigma(u,v,0) \mathbf{n} < 0, (u,v) \in \Omega_c \} \\ \Omega_c &\leftarrow \Omega_c \cup \Omega_c^{incl} \setminus \Omega_c^{excl} \end{split}$$

**until**  $\Omega_c$  does not change

#### 3.5.3 Computing variation

**Strain fluctuation.** In 3D objects with a nonzero curvature, the simulated maximum compressive strain field indicates two independent properties: the global object shape, indicated by the large-scale, global changes in strain across the surface; and the texture, which is results in small-scale local *fluctuation*. An object with zero curvature has a negligible change in global strain, resulting in a globally flat strain field; however, curved surfaces elicit a varying strain field that reflects the global shape of the curved surface, as shown by the blue



Figure 3.15: For curved objects, we must find an updated strain field that eliminates effects from large-scale shape. As shown in blue, the original strain field changes over the surface, according to the convex object shape. However, when we compute and subtract the strain field of the same non-textured convex shape (green), we acquire the texture strain *fluctuation* field without any effects from shape (red).

curve in Figure 3.15. If our model is to be used directly on curved surfaces, we must separate the qualities of shape and texture and eliminate effects from shape when computing the texture roughness. Thus, we propose a strain fluctuation variation model, which eliminates effects in the maximum compressive strain field caused by changes in large-scale shape.

Given a textured surface, we first compute the maximum compressive strain field as described in the previous section. We also compute the maximum compressive strain field for a *non-textured* surface with the same global curvature. We subtract this non-textured strain field from the original strain field to find an updated field that eliminates effects from large-scale shape. A two-dimensional simulation example is shown in Figure 3.15. Note that as described below, we take the variation, or absolute difference, between points on this field; therefore, the change in magnitude across the whole field does not have an effect on the final value.

Roughness may be measured on input geometry (e.g., acquired by scanning) that is not initially separated into a smooth base surface and a displacement field. Spectral domain provides a natural way to perform this separation by extracting the low-frequency part



Figure 3.16: For each texture simulation, the maximum compressive strain profile was obtained for a depth of 0.75 mm. To find the strain variation, pairs of sample points (shown in red) were chosen from inside sampling areas (shown in yellow) with radius r separated by distance d. The mean absolute difference of all such pairs is defined to be the mean strain variation. Mean strain variation was found to match perceptual estimates of roughness.

below the texture frequency. Typically, however, the input samples can be obtained in a flat form; for tasks like texture synthesis and application of an existing texture to a surface, no adjustment of roughness is needed as long as the curvature is not extreme.

**Strain Variation** From the maximum compressive strain fluctuation field, we take a set of random samples. Previous works have suggested taking an interval of 2.2mm Connor et al. (1990) or anywhere from 1 mm to 3 mm Yoshioka et al. (2001). In reality, mechanoreceptors occupy random locations in the skin according to an average density, and a single neuron may be informed by multiple branching receptors. Thus, our sample pairs do not have a single exact spacing; instead, we take samples randomly from radii r separated by a given distance d, as shown in Figure 4.5. We take 8000 random sample pairs across a  $8 \times 8$ mm area in the center of the simulation area (to avoid unwanted effects from the edges). From these pairs we find the mean strain variation, the average absolute difference in maximum compressive strain at those point pairs. We found the optimal sampling for our perceptual



Figure 3.17: Comparison of roughness values found by four different methods suggested in previous work ( $R_a$ , 90th percentile, GLCM sum of squares, and GLCM variance) and our method (strain variation). Our method produces the best fit, with an R value of 0.91. The bump textures are shown in green dots, and the natural textures are shown in blue dots.

data to be d = 0.8, r = 0.8, which resulted in a coefficient of correlation R = 0.91. As a note, many other samplings also produced good fits, with correlation coefficients greater than 0.85 (see Figure 3.18).

#### 3.5.4 Results

The results of our method and a comparison to several measures suggested in previous works are shown in Figure 3.17.  $R_a$  is the arithmetic average of absolute values of heights, a simple roughness parameter commonly used in profilometry that has also been used to



Figure 3.18: Left: the model is relatively insensitive to small changes in applied force, but the fit worsens for large changes. Right: The model fit is relatively insensitive to change in the choices of sampling distance and radius; the fit changes slightly but still has a correlation over 0.85 for all values tested.

estimate perceptual roughness in many works, e.g. Chen et al. (2009). 90th percentile height, GLCM sum of squares, and GLCM variance were suggested by Elkharraz et al. (2014) as close estimates to perceptual roughness. Our strain variation roughness measure performs significantly better than any of the other measures.

Model sensitivity To test whether this model is stable with respect to the force and sampling parameters, we recomputed the fit with small changes to these variables (Figure 3.18). As shown on the left, the model is relatively insensitive to changes in the simulated force. Good fits are still produced within a range of 50-200% change in force from our choice of 10N. The model may fail if the force is very high or low, likely because the contact area changes significantly. As shown on the right, our model was also found to be insensitive to changes in the sampling parameters; we tested a large range of sampling parameters, and all resulted in a correlation of R > 0.85.

**Texture homogeneity** In this chapter we define the word *texture* as a somewhat homogeneous surface, which has a consistent roughness across all areas. The textures we used as stimuli seemed homogeneous in appearance, but we also wanted to determine whether the textures were homogeneous in tactile roughness. To this end, we computed the roughness of each surface on fifty 5mm square sliding windows across the span of the surface. We then



Figure 3.19: Fit for the data excluding the five textures shown in red, which had significantly higher variance in calculated roughness across the surface.

computed the variance of the computed roughnesses in proportion to the average roughness of the surface. Most textures had a very small variance, on the order of  $10^{-4}$ . Five natural textures had significantly higher variance, greater than  $10^{-3}$ . These textures are highlighted in red on Figure 3.19. The calculated R correlation value excluding these textures is slightly improved, at R = 0.965. We posit that the inhomogeneity of these textures may have caused subjects difficulty in determining the roughness consistently across the surface; when touching different regions of the textures, subjects may have perceived contradictory results.

**Curved surfaces** Figure 3.20 shows results of the strain fluctuation variation model for curved surfaces with the three textures tested in Section 3.4. For each of the three textures, the predicted roughness of ten different curvatures was compared against the roughness of the uncurved texture, and the percentage difference from the uncurved texture was calculated. As expected, the percentage difference between the curved and flat texture was typically below the 19% threshold, except in the case of high curvatures.



Figure 3.20: For the three textures used in section 3.4, the percent difference in simulated roughness was calculated between the flat texture and curved textures of different radii. The percent difference is typically below the 19% threshold (the black dashed line), with the exception of very high curvatures (less than 10mm for concave surfaces, and less than 3mm for convex surfaces).

# 3.6 Applications

Applying particular tactile textures to fabricated objects is useful for both functional and aesthetic reasons. Many everyday objects have a tactile texture, including figurines, grips and handles, buttons, and other parts of objects that are used for interaction. While past work, e.g. Torres et al. (2015), has been interested in applying tactile textures to objects, they did not use a specific perceptual model. Our model can be used to confer more precise and more diverse roughness characteristics to fabricated objects.

In this section we describe several applications illustrating how our model can be used in fabrication. We first show that it can aid in the process of choosing textures to fabricate a 3D object with a desired roughness. Second, we show how our scaled perceptual model can be used to fabricate representations of visual images using distinct tactile properties in the place of distinct visual properties, such as color. Lastly, we demonstrate how our general model can be used to manufacture unique combinations of visual and tactual properties.



Figure 3.21: Two models, the gecko (left) and key cap (right), were fabricated with two textures each. Fabricated models have height textures scaled to have different tactile roughnesses, as matched against the standard set.



Figure 3.22: a) Hedgehog with a rough bump texture that feels spiky; b) Screwdriver handle with a moderately rough bump texture for easy and comfortable gripping; c) Spinning "fidget ring" with rough cloud texture.

**Heightmaps and roughness** Often, users desire to apply a given height map to a texture to confer both visual and tactual properties; however, until now, it has been difficult to predict or alter the tactile properties of a visual height map. Using our model, we can make small changes to the scale or height of a heightmap to preserve the appearance while drastically altering the tactile roughness. We show two examples in Figure 3.21. First, a gecko model (WebmasterZero (2016)) is given different displacements of the same "lizard skin" texture and three of the "burlap" texture. By altering the scale of these textures, we produce three different geckos, each with distinct tactile roughnesses.

We also produce a second model, a textured key cap of the type used for key identification; the texture enables the key to be identifiable in the dark. The key caps are textured with two scaled versions of the "leather" heightmap and three of the "foam" heightmap, and each of these occupies a different perceptual roughness.

Additional examples of fabricated tactile objects are shown in Figure 3.22: a hedgehog model with a rough bump texture; a screwdriver handle with a moderately rough texture, and a spinning "fidget ring" with a rough cloud texture.

**Tactual images** Producing tactual images is of interest not only for aesthetic reasons, but also for practical reasons relating to accessibility: people who are blind can greatly benefit from textured representations of images, e.g. picture books, educational materials, or works of art (Theurel et al. (2013)). We use the roughness scale generated by our model to identify sets of textures which have significantly different tactile roughness. In this way, we can replace the colors in images with distinct textures, so that the colors can effectively be perceived tactually. Figures 3.23 and 3.24 show examples of images fabricated in this way. As shown in the center panels, the chosen textures are distinct from one another by an interval larger than the threshold of discrimination.

**Controlling visual and tactile properties independently** To demonstrate the control over tactile properties our model affords, we consider two examples: visible variation in a geometric texture which is perceived as tactually homogeneous, and conversely, an invisible variation in texture producing a variation in tactile perception.

For the first example, we manufacture several bump texture plates that feel like uniform textures; however, the non-contacted parts of the model are altered to produce a visual feature on the model, i.e. a feature that can be perceived visually but not tactually.

Similarly, we show that we can manufacture an object that has a consistent visual appearance but contains a hidden tactual characteristic. We manufacture the same plates, using the variation in texton height which produces strain differences, so that the difference cannot be clearly seen but the shape outlines can distinctly be felt.

These plates, fabricated with visible or tactile shapes, are shown Figure 3.25 and Figure 3.26.

In an informal experiment, 8 subjects were presented with the tactile plates in Figure



Figure 3.23: From an original image (a), a depiction of a lion was created using two different roughnesses to correspond to the colors (b). The fabricated model is shown in (c). (The black image outlines are represented as smooth raised lines).

3.25 either in a visual or tactile context, and asked to identify whether a shape was present on the plate. On the tactile plates (Figure 3.25, right), all subjects were able to tactually identify the presence of shapes, and in most cases could identify the specific shape (the cross shape was most difficult to discern); in the visual plates (Figure 3.25, left) subjects did not tactually perceive any shape. Similarly, subjects could not visually identify specific shapes in the tactile plates, but they were able to clearly see the shapes on the visual plates.

# 3.7 Conclusion

We have presented a perceptually-based model for evaluating tactile roughness of surface textures. Using perceptual experiments with 46 different surface textures, we found that the perceptual space for roughness fits well in one dimension, and we used this space to create a physically-based perceptual model for evaluating tactile roughness. We demonstrated how this model can be used to predict or compare the tactile roughness of fabricated objects, to select surface textures with different roughness, and to create textures with unique combinations of visual and tactile features.



Figure 3.24: A representation of De Stijl-style geometric artwork (a) was created using five different easily-distinguishable roughnesses (b) to represent the five colors. The fabricated model is shown in (c).



Figure 3.25: Textured plates with visual (left) or tactile (right) renderings. The top row shows the rendered models; the middle row shows the 3D prints; the bottom row shows a visual representation of the tactile strain map. The left panel shows four texture plates with visible features that cannot be perceived tactually. Conversely, the right panel shows the same four shapes which cannot be seen but whose outlines can be felt, as seen in their strain profiles.



Figure 3.26: Textures can be produced that contain hidden visual or tactual messages.

#### 3.7.1 Limitations and Future Work

Our model only applies to large-scale roughness. Our stimulus set was limited to a single material and a minimum feature resolution, as our 3D printer tends to smooth small features, so fine features (i 0.2 mm) were not possible to test. As mentioned in Section 3.5, our model only applies to homogeneous textures, which feel the same over the surface; in practice it may give incorrect results for non-homogeneous textures. However, our model also naturally provides a method of testing whether a texture is homogeneous. While our provided model relies on our experimental evidence that curvature does not have a significant effect on roughness perception, we note that results may be different for extreme high-curvature objects where contact area is small.

Our model represents a simplification of the mechanosensory system. In reality, the skin is not a uniform substrate; its structure is non-isotropic and layered, and it has complex, nonuniform geometry, e.g. fingerprint ridges. While our model appears to work well, it may be improved by more closely simulating the skin structure and mechanosensory mechanics.

Our model requires FEM simulations to evaluate a roughness estimate for a texture. It would benefit, at minimum, from precomputing the roughnesses for the desired set of textures. However, we believe that one can extract an adequate approximation for the map f(H) from running multiple simulations and using machine learning techniques to predict the roughness value directly from height map data.

To aid in the fabrication process, our model and reference stimuli could be integrated into an existing tool such as Torres et al. (2015) to provide more precise predictions of tactual roughness when modeling a fabricable object. Fabricating objects with different roughnesses and other tactual properties, such as weight or compliance, would create interesting stimuli for future studies of perception.

Finally, as our model performs significantly better than existing methods to obtain tactual

roughness, it also has broad implications for other fields of work: in addition to use in psychophysics and neuroscience, it may also be of use for virtual haptics, robotics tactile perception, and many other fields with an interest in perception or tactual properties.

# 3.8 Chapter Notes







#	Name	Render	#	Name	Render
23	Foam		24	Leather	
25	Lizard		26	Plaster	
27	Skin		28	Stucco	
29	Styrofoam		30	D1	
31	D14		32	D66	
33	Backpack		34	Bark	

-	#	Name	Render	#	Name	Render
-	35	Cloth		36	Concrete	
	37	Crab		38	Frog	
	39	Granite		40	Grasshopper	
	41	Inverted leather		42	Metal grate	
	43	Paper		44	Skirt	
	45	Strap		46	Wool	

# Chapter 4

# Appearance-Preserving Tactile Optimization

This chapter provides an extension of the previous work, by developing an expedited method to simulate touch and compute tactile roughness, using machine learning techniques. The fast computation is used for constrained optimization to preserve the appearance of a texture while altering its tactile feeling. This chapter was a collaboration with Denis Zorin; all work presented in this chapter is entirely my own.

# 4.1 Introduction

Tactile textures are ubiquitous in everyday life. We encounter tactile textures on the surfaces of fruits and plants, skin, woven fabrics, and many manufactured surfaces. Tactile texture often serves a specific purpose, practical or aesthetic (an object should feel good, not just look good). Creating a particular tactile feeling is a common task which receives less attention than visual appearance, although is often just as important. Tactile feeling plays a particularly important role for people who are visually impaired, who rely on the sense of



Figure 4.1: Our optimization procedure enables the control of a texture's tactile roughness while maintaining its visual appearance. Starting with a target texture (left), the procedure optimizes toward a desired tactile roughness while preserving the visual appearance (center). The resulting textures can be used to fabricate visually similar but tactually different objects, such as these 3D-printed starfish (right).

touch much more.

The tactile feeling and visual appearance of objects can interact in unpredictable ways; for example, the tactile texture may be a byproduct of creating a particular appearance (e.g., an etched pattern), or vice-versa (e.g., knurled grips have a particular look). The goals of achieving particular visual and tactile appearances may be conflicting: e.g., one may want a particular visual pattern on a tool handle, while achieving specific tactile properties optimal for usability. While in many cases, little can be done about the interaction of visual and tactile properties, advanced fabrication technologies like high-resolution 3D printing enable highly flexible control of both visual and tactile texture.

A characteristic feature of both visual and tactile textures is their statistical nature: that many distinct patterns and geometries may look or feel the same. We refer to distinct (in the sense of per-point equality) textures that are perceived in a similar way as perceptually equivalent. The large space of perceptually equivalent textures makes it possible to adjust one aspect of a texture (e.g., tactile) without affecting the other (visual). This type of adaptation makes it possible to separate the process of visual and tactile design.

In this chapter, we propose a method for independent control of tactile feeling and visual appearance of an object. More precisely, the problems we solve can be formulated as follows: given input texture geometry, how can we modify it to achieve certain target tactile properties while minimizing changes to its visual appearance? And conversely, how can we achieve specific visual appearance by modifying geometry, while preserving tactile properties? Our method builds on the previous work on quantitative modeling of perceptual roughness, as well as visual appearance perception. One of the main drawbacks of the highly accurate roughness model we use is the relative expense of its evaluation and the lack of differentiability, making it difficult to apply in the optimization context. One of the main contributions of our work is an efficient neural network-based differentiable version of the model for roughness. This model is in close agreement with the relatively expensive-to-evaluate model, while it also does not require expensive 3D meshing and FEM simulation and can be evaluated directly on the input texture geometry. The speedups we obtain are on the order of 10,000 times for roughness evaluation (although the original FEM model we compare to was not optimized). making it possible to evaluate roughness at interactive rates. In addition, the resulting model provides gradients, making it trivial to plug it into an efficient optimizer.

We have also constructed a similar neural network model for a visual similarity measure for geometric textures, involving advanced lighting effects, also with multiple orders of magnitude speedups.

Using these models, we developed an optimization method that allows a balancing of the changes between visual appearance and tactile roughness, as well as applying the same approach to another aspect of tactile perception, temperature sensation. We demonstrate the behavior of our system for a variety of examples in different contexts.

## 4.2 Related Work

Our work is related to previous work in several domains. Two of the most important works we build on are Tymms et al. (2018) (we use the roughness model described in that chapter as a starting point), and Isola et al. (2017), which describes an image-to-image CNN that we adapt to our purposes. Our work is connected to a spectrum of work in visual and tactile perception modeling, texture synthesis and applications of CNN to optimization.

Tactile perception. Research on the sense of touch has found that tactile perception consists of 4-5 dimensions (Tiest (2010)), including large-scale and small-scale roughness; compliance; friction; and temperature. Here we focus on large-scale roughness, elicited by features larger than 0.1 mm in size and detected through strain; we also consider temperature, controlled here by mediating the area of contact between the skin and a surface. Most previous research in roughness perception has used different types of natural or artificial stimuli that are difficult to control, e.g. Manfredi et al. (2014), Connor et al. (1990). We use 3D printing to allow creation of higher-resolution, more precisely controllable surfaces. We also gain insights from Tiest and Kappers (2009b), who performed experiments on temperature perception based on the thermal diffusivity and found a relative threshold of discrimination of 43%.

**Tactile fabrication.** Piovarči et al. (2016) developed a quantitative model for tactile *compliance* perception using stimuli fabricated from materials with different perceived tactile compliance, and demonstrated its applications to fabricating shapes with variable properties. Compared to roughness, compliance rarely affects the visual appearance of an object, so combining the two is relatively straightforward. In Elkharraz et al. (2014) a roughness model was obtained using *tactile* textures fabricated from a set of *visual* textures converted to shallow height maps, implicitly creating a close connection between visual and tactile appearance. In our work, we aim to decouple these.

Other recent work in the fabrication domain has aimed to facilitate the incorporation of tactile properties in 3D printed models. Torres et al. (2015) provides an interface to fabricate objects with a user-specified weight, compliant infill, and rough displacement map. However, their roughness metric relies on texture feature size, which is not always definable and does not provide a comprehensive model for all textures. Chen et al. (2013) develops methods to fabricate objects with specified deformation behavior and textured surface displacement, but does not allow direct perceptual control. Degraen et al. (2019) addresses a more specific question using 3D-printed hair structures to adequately simulate material roughness and softness for use in immersive virtual reality.

Thermal conductivity is of interest in fabrication but is typically controlled by altering the base material or creating a composite; Wang et al. (2017) reviews several options to vary thermal conductivity and other material properties. We aim to control conductivity for tactile contexts by altering geometry. In a related application, Zhang et al. (2017) optimizes the tessellation pattern of 3D-printed orthopedic casts for thermal comfort.

**Texture synthesis.** Portilla and Simoncelli (2000) created a model for texture synthesis based on a set of image statistics. Their method performs well on many natural and artificial textures, but fails on many others; it also requires a significant amount of time and is therefore poorly suited to optimization. Wallis et al. (2017) is based on CNN feature-based model (VGG-19) but similarly does not provide a close match for many textures. Classical non-parametric texture synthesis work, e.g. Efros and Leung (1999);Wei and Levoy (2000), yield high-quality results for many textures, but are not readily adaptable for our optimization purposes. A recent survey of synthesis methods can be found in Barnes and Zhang (2016). Works such as Gatys et al. (2015) and Ulyanov et al. (2016) present synthesis methods based on CNNs but are not robust enough for our optimization purposes. Zhou et al. (2018) presents a recent GAN-based texture synthesis method with impressive results, but it requires several hours of training for each image, and is therefore not suitable for optimization. In contrast, we seek a method that is robust for all textures, and whose loss computation does not require a large amount of time.

**Optimizing fabricated visual appearance.** Several works use optimization to accomplish a similar goal of appearance preservation for 3D printing. Schüller et al. (2014) uses optimization to alter the geometry of 3D objects to maintain visual appearance subject to other geometric constraints, to produce bas-reliefs for fabrication. Rouiller et al. (2013) designed a pipeline to optimize a 3D printed surface's microgeometry to replicate a desired BRDF. Elek et al. (2017) employs optimization to correct for light scatter to more accurately reproduce color in 3D printing, and Shi et al. (2018) uses optimization of the internal layer structure of color multimaterial 3D-printing to replicate the full spectrum of color of 2D art, invariant to illumination, more accurately than traditional 2D printing.

Visual similarity of images and textures. Visual similarity metrics are designed to quantify perceptual similarity, with consistency with perception measured by pairwise or three-way comparisons: if the numerical indicator of similarity for one pair of images is higher than for another, then we expect the first pair to be perceived as more different. Well-established visual metrics include those based on *structural similarity*: SSIM Wang et al. (2004), FSIM Zhang et al. (2011), MSSIM Wang et al. (2003). A different metric designed primarily for evaluation of image compression quality, and based on a complex visual system model, is found in Mantiuk et al. (2011). Zhang et al. (2018) presents a metric based on deep features learned for, e.g., a classification task and combined with a simple metric in the feature space. These metrics were demonstrated to be closer (on relevant datasets) to human perception compared to SSIM. We use a simple, tighter metric based on surface normals discussed in Section 4.3. We discuss our experiments with other measures there. This is

consistent with some of the work on depth images, e.g., Haefner et al. (2018) a method for increasing resolution of depth images using an additional color channel, uses a metric including estimation of the normal difference.

Neural networks in model reduction. Model reduction is a well-established area which was using a variety of machine learning-related techniques to decrease the number of parameters needed to simulate a physical model, with the goal of reducing the cost of the simulation, which is particularly important in optimization context. We share this motivation, although we do not aim to achieve this goal through explicitly reducing the number of parameters of the model. Older methods are relatively well-covered in the survey Forrester and Keane (2009). Very recently, and concurrently to this work, neural networks were applied for reduced-order modeling of Poisson and fluids in 2D Hesthaven and Ubbiali (2018). Other model examples are considered in Raissi et al. (2019).

**Steganography.** Steganography algorithms aim to hide watermarking or other types of information in data, with a few papers focusing on 3D data; see e.g., Wang et al. (2008) for a survey, and more recently Yang et al. (2017). As we do in our work, these methods aim to preserve visual appearance, but the goal is to conceal the hidden information from the naive observer; in our case, we do not want to make the modification of tactile properties apparent.

## 4.3 Overview

The main goal of this work is to develop a process to allow the control of a texture's tactile roughness or tactile temperature while maintaining its visual appearance, which can produce a range of effects.

**Summary** Given an input 2D height field and a desired tactile roughness value or contact area, the model uses learned functions – one for appearance, based on rendering; and one either for tactile roughness, based on variation of strain in simulated skin, or for tactile temperature, based on a simulated skin contact area – to perform an optimization for roughness or contact area while minimizing visual distortion. We use psychophysical experiments to validate the results. A general overview of the process is shown in Figure 4.1.

The development of our optimization process consists of the following steps:

- We create a set of 6300 height maps comprising a variety of textures and grayscale images. We run simulations estimating the human finger contacting these heightmaps, and find the resulting field of maximum compressive strain.
- We use a convolutional neural network to learn a function taking the input heightmap and outputting the maximum compressive strain field, and we compute tactile roughness on this field.
- We use a similar neural network to learn a function taking the input heightmap and outputting the contact area between the skin and the texture.
- We learn a function for the height field's visual appearance using a CNN to learn heightfield rendering with shadow and lighting.
- We develop an optimization procedure taking the losses from the learned roughness or contact function and the learned rendering function to optimize for a target tactile roughness or temperature while minimizing change in appearance.
- We validate this procedure by testing several textures both as renderings and as 3Dprinted textures and running human experiments. For roughness, we compare against the simpler method of altering tactile feeling using linear scaling.

# 4.4 Optimization

The optimization procedure acts to alter the geometry of the input texture height field, in order to modify the tactile feeling of the input while minimizing its change in visual appearance.

#### 4.4.1 Optimization Overview

We use three functions in our optimization process to compute tactile and visual difference estimates:

- Roughness: φ<sub>r</sub> : ℝ<sup>n</sup> → ℝ<sup>n</sup>, where n is the number of pixels in the height and stress maps, mapping the height field to stress magnitudes at a plane inside the skin where tactile sensors are located. The stresses are sampled at the same resolution as the input height field.
- Visual appearance: φ<sub>v</sub> : ℝ<sup>n</sup> → ℝ<sup>kn</sup>, mapping the height field to the pixel values of k rendered images with different lighting.
- Contact area:  $\phi_c : \mathbb{R}^{2n} \to \mathbb{R}^n$ , where *n* is the number of pixels in the height and contact maps, mapping the height field and corresponding strain field to the distance between the skin and the surface at each point.

In addition, we use a function  $R : \mathbb{R}^n \to \mathbb{R}$ , to evaluate the perceptual roughness estimate from the stress field  $\sigma = \phi_r(H)$ .

Using these functions, which we define precisely below, our target functional is defined as follows. For a given input texture height field  $H_0$ , and target perceptual roughness  $r_{trg}$ , target contact area  $c_{rg}$  and target height range  $[0, H_{trg}]$  we define the following energy terms:

1.  $E_{rough}(H) = |r_{trg} - V(\phi_r(H))|$ : the difference between the current roughness and the target roughness, with the strain variation function V defined in Section 4.4.2.
- 2.  $E_{contact}(H) = |c_{trg} A(H))|$ : the difference between the current contact and the target contact, where A is the weighted contact distance function defined in section 4.4.3.
- 3. E<sub>vis</sub>(H, H<sub>0</sub>) = <sup>1</sup>/<sub>n</sub> ||φ<sub>v</sub>(H<sub>0</sub>) − φ<sub>v</sub>(H)||<sub>2</sub>: the visual difference, computed as the L<sub>2</sub>-norm of the pixel-wise difference between the current rendered image and target rendered image. Two different rendering conditions are used for this computation, and the results are added.
- 4.  $E_{reg}(H) = \frac{1}{n} \|\Delta_x(\phi_v(H_0) \phi_v(H))\|_2 + \|\Delta_y(\phi_v(H_0) \phi_v(H))\|_2$ : the difference variation regularization energy, where  $\Delta_x$  and  $\Delta_y$  are finite difference matrix operators for horizontal and vertical directions; i.e., an approximation of  $\int \|\nabla(\phi_v(H_0) \phi_v(H)\|_2 dA$ .
- 5.  $E_{clamp}(H) = ||H clamp_{[0,H_{trg}]}(H)||_2^2$ : the clamping energy to keep the result in the  $[0, H_{trg}]$  range.

The total energy we minimize is defined as

$$E(H, H_0) = E_{rough}(H) + w_1 E_{vis}(H, H_0) + w_2 E_{reg}(H, H_0) + w_3 E_{clamp}(H)$$
(4.1)

To optimize this function efficiently, we need to compute  $E(H, H_0)$  as well as  $\nabla_H E(H, H_0)$ efficiently. However, computation of  $E_{rough}$  involves a 3D finite element simulation, including 3D domain meshing and contact resolution; computation of  $E_{vis}$  requires rendering of textures with some global illumination effects.

We approximate  $\phi_r$ ,  $\phi_c$  and  $\phi_v$  using neural networks addressing both of these problems, as these provide (a) fast evaluation of function values (b) evaluation of derivatives with respect to the input parameters. The details of these approximations are discussed below.

Convergence criteria and weight choices. The main parameter of the optimization is  $w_1$ , controlled by the user, which represents the trade-off between visual fidelity and approximating the target roughness.

The weight  $w_3$  is chosen to be relatively high,  $10^5$ , so that the last term operates as constraint. The weight  $w_2$  is chosen to be lower compared to  $w_1$ , as  $E_{var}$  acts as a regularizing term, picking smoother solutions among those with low values of the first two terms. We use  $w_2 = 0.06$ .

For contact area, which has values on the order of  $100mm^2$ , approximately 1000 times the typical roughness values, these weights were scaled up by 1000.

We use a stopping criteria for optimization that places bounds on three of the energy components: For roughness,  $E_{rough} < \varepsilon_r r$ , with  $\varepsilon_r = 0.1$ , about half of the 19% threshold for tactile roughness discrimination described in Tymms et al. (2018). For visual difference,  $E_{vis} < \varepsilon_v ||\phi_v(H_0)||_2$ , with  $\varepsilon_v = 8$ , experimentally found as a conservative goal to avoid visible changes, corresponding to a 2% change in pixel values.

The height constraint is expected to be satisfied nearly precisely:  $E_{clamp} < \varepsilon_c$ , with  $\varepsilon_c = 10^{-4}$ . We define  $H_{trg} = 3$ , indicating that the height must remain below 3mm, selected as a reasonable maximum height for a fabricable tactile texture.

An example of the optimization process for a texture is shown in 4.2. The effect on convergence of using altering the weights is shown in Figure 4.3.

The Adam optimizer (Kingma and Ba (2014)) implemented in Pytorch is used for optimization. A learning rate of 0.027 was chosen through trials with single parameters to permit convergence of the parameters but avoid excessive oscillation. In the next sections, we explain how the roughness, contact and visual functions, respectively  $\phi_r$ ,  $\phi_c$  and  $\phi_v$ , are defined.



Figure 4.2: Parameter convergence during optimization for roughness and visual appearance. The goal is to alter the roughness of the input texture (iteration 0) while preserving its visual appearance, which is done by the final iteration.



Figure 4.3: a) When a significantly (10x) lower weight is used for  $w_1$ , convergence of roughness to the target may not occur. b) A significantly higher (10x) weight for  $w_1$  causes the visual energy to converge more slowly, and it may not reach the target threshold.



Figure 4.4: In the original roughness model, a 3D FEM simulation was used to simulate the skin touching a textured surface, and the maximum compressive strain field was sampled from a depth of 0.75 mm.

## 4.4.2 Tactile roughness

We use a modified version of the model developed in Tymms et al. (2018), which computes the tactile roughness of a surface by simulating the strain variation field resulting from skin contact on the surface. The computation of the model is relatively expensive; we briefly summarize the model here for completeness. The main step of the model is a finite element method simulation of the contact of the skin with the tactile texture defined by H(x, y), to obtain a corresponding displacement field  $\mathbf{u}_H(u, v, w)$ , where u, v, w are 3D coordinates in the undeformed layer of skin, with w = 0 corresponding to the surface, and  $w_0 = 0.75mm$ corresponds to the approximate depth of the tactile receptors.

To approximate the skin, we use a two-layer block model, which represents  $1cm^2$  in surface area and 0.5cm in height. The lower half of the model has a Young's modulus of 0.042 MPa, representing all tissue; and the upper half, representing the bone, has a Young's modulus of 18000 MPa. The force used for this model was 10 N, found in pilot experiments in which subjects touched textured surfaces placed on a force sensor. A model of the simulation is shown in Figure 4.4.

For a displacement field  $\mathbf{u}$ ,  $\epsilon[\mathbf{u}] = \frac{1}{2}(\nabla \mathbf{u} + \nabla^T \mathbf{u})$  is small-deformation strain tensor. If  $\lambda_3(\epsilon)$  is the largest-magnitude negative (compressive) eigenvalue of the strain tensor, our

perceptual roughness estimate f(H) can be written as

$$f(H) = \mathcal{V}(\lambda_3(\epsilon(\mathbf{u}_H(\cdot, \cdot, w_0))))$$

where V is the strain variation function on the plane  $w = w_0$ . We replace a stochastic function defined in the original model with a deterministic function described in more detail below.

The expensive step is the computation of displacements  $\mathbf{u}_H$  for a given H: it requires sufficiently fine 3D meshing to resolve the detail at the scale of smaller texture features, and solving a nonlinear (due to contact) constrained elastic deformation problem, which in our current implementation has a computation time of 20-40 minutes and uses 15GB of memory when using the required highly-refined mesh. In addition to the cost of evaluation, it is difficult to obtain an approximation of the derivative of this function other than by extremely expensive finite differences, so optimizing a functional depending on the  $\mathbf{u}_H$  can only be done with gradient-free methods.

This is the step that we replace with a direct map

$$\phi_r(H)(u,v) \approx \lambda_3(\epsilon(\mathbf{u}_H(u,v,w_0))),$$

represented with a neural network.

Strain variation function. In Tymms et al. (2018), the strain variation function  $V(\sigma)$ was computed as follows: a large set S of N randomized pairs of samples  $(p_1, p_2), p_i = (u_i, v_i)$ , separated, on average, by a distance d, are computed. Denoting  $\sigma(u, v) = \lambda_3(\epsilon[\mathbf{u}_H](u, v, w_0))$ ,

$$V(H) = \frac{1}{N} \sum_{(p_1, p_2) \in S} |\sigma(u_1, v_1) - \sigma(u_2, v_2)|$$

N = 8000 sample pairs were used, sampled from disks of radius 0.8mm placed at the endpoints



Figure 4.5: a) Original random sampling; b) Equivalent deterministic sampling

of randomly selected segments of length 2.2mm.

Instead of using a random sampling of points, we use a deterministic evaluation of variation between each point and its neighbors within the desired distance, in order to derive a strain variation field (Figure 4.5):

$$V(H) = \frac{1}{2rl} \int_{x=0}^{l} \int_{y=0}^{l} \int_{\Delta=d-r}^{d+r} \int_{\theta=0}^{\pi} |\sigma(x,y)| -\sigma(x+\Delta\cos\theta, y+\Delta\cos\theta)| dxdyd\Delta d\theta$$

$$(4.2)$$

This function is smooth, so the gradient of the complete roughness estimates can be computed.

Learning the strain field. The FEM simulation used to compute  $\sigma(u, v)$  in Tymms et al. (2018) is used solely to find a single 2D strain field; that is, the simulation takes as input a 2D grid (the heightmap defining the boundary conditions for the contact area), and returns as output a 2D grid (the maximum compressive strain at a depth of 0.75mm). Image-to-image translation problems have been studied extensively in machine learning, and here we adapt a convolutional neural network described in Isola et al. (2017) to learn a relationship  $\phi_r$ between the input height map and the output maximum compressive strain.

To acquire ground truth simulation data, we ran the FEM simulation for the 3D skin



Figure 4.6: Two examples from the test set of the learned CNN, showing learned and groundtruth maximum compressive strain fields computed from heightmaps (Strain fields are shown with rescaled contrast for visual clarity).

model using a heightmap dataset of with 6307 image pairs, similar to the size of several datasets successfully trained with this neural network structure. We use a set of black and white images and textures (including the Describable Textures Dataset Cimpoi et al. (2014), VisTeX MITMediaLab (1995), and Brodatz texture database Brodatz (1966)) and procedural textures to enrich the dataset. In some cases, images were randomly cropped and/or scaled, and in some cases procedural noise was added. Heightmaps had a maximum vertical height of 3 mm and represented a texture of size 100  $mm^2$ . As suggested in Tymms et al. (2018), for each simulation we found the maximum compressive strain field at a depth 0.75 mm, and the strain field of a flat texture simulation was subtracted to discount any effect from edges.

Inputs and outputs were scaled to  $128 \times 128$  px images. The set was split randomly into three sets: testing (312 images); training (4918), and validation (1077). We used the convolutional neural network used as the generator in Isola et al. (2017), with no dropout and using BCE loss, and trained for 200 epochs with batch size 1.

The learned strain field and its resulting tactile roughness value were computed from an unseen testing set, and the learned value was compared against the actual value. The median error in roughness was 5.3%, and the average error was 8.0%, well below the perceptual



Figure 4.7: The difference in computed roughness between the learned strain field and the real strain field is typically very low, with a median of 5.3%.

threshold of 19%. These values are well below the threshold of discrimination of 19% described in Tymms et al. (2018). The error distribution is shown in Figure 4.7.

The network allows the roughness to be computed in an average of 0.05 seconds, a significant speedup compared to the 20-40 minutes required to run the full FEM simulation.

The learned function and its gradient are used in optimization for a texture to converge toward a desired tactile roughness, as shown in Figure 4.2.

#### 4.4.3 Contact area

Computing the contact area requires the same time-intensive FEM simulation as computing the roughness field. To compute the contact area, we use a function taking as input the height field and outputting the field of distances between the surface and the simulated skin at each point. The computation of this distance field is expensive and requires an FEM simulation as described in section 4.4.2. Therefore, we replace this step with a neural network.

Learning the contact distance field. The FEM simulation takes in the input height field H and outputs a mesh displacement field  $\mathbf{u}_H$  describing the displacement of the skin when in contact with height field H. From this displacement field and the height field, we can acquire the field of the distance  $\mathbf{d}$  between the skin and the input texture at each point, where a distance of 0 indicates skin contact with the texture surface.



Figure 4.8: The contact area function takes as input the input heightmap (left, red channel) and the strain field (left, green channel) and outputs the distance field (center, where black indicates a distance of 0). The distance field can be used to compute the contact area (right, where the contact area is black)



Figure 4.9: The learned contact area matches the actual contact area very closely, with an error of 2.7%.

We adapt a similar convolutional neural network to learn the relationship between the input height map H and the output distance field  $\mathbf{d} = \phi_c(H)$ . We used the same height field training set as used previously in Section 4.4.2, which had about 6300 pairs. To improve the accuracy of the learned function, we also provided the strain field as input, so that the input to the function has 2 channels of input: the height field and the strain field. An example of the function's input and output is shown in Figure 4.8.

To compute the error for the testing set of size 250, the learned distance field was computed for each input heightmap with its learned strain fields, and the contact area was computed and compared to the actual contact area derived from simulation. The errors in computed contact area for this set had a mean of 2.7%, as shown in Figure 4.9. **Contact optimization** The optimization aims to modify a texture so that its total contact area moves to a particular target. Because contact area itself is a discontinuous function, the optimization process was often unable to converge. Therefore, we use a smooth function weighting the contact area at each point proportionally to the inverse of its distance. That is, for contact distance field **d**, contact area is approximated by:

$$A(H) = \int_{x=0}^{l} \int_{y=0}^{l} \frac{1}{1+80 * \mathbf{d}(x,y)}$$
(4.3)

This function provides a smooth weighted contact distance, so that a distance of 0 has a weight of 1; weights decay rapidly so that a distance of 0.01 mm has a weight of 0.5 and a distance of 0.1 mm has a weight of 0.1.

## 4.4.4 Visual appearance

To preserve a texture's visual appearance during optimization, we use a custom function based on visual similarity of the original height field, and the optimized one. Ideally, to measure visual similarity, we would consider all possible views of a pair of textures, under different lighting conditions, and apply a visual difference metric between each pair, and compute an aggregate metric. We follow these steps but for a restricted set of lighting conditions and using the simplest visual metric to compare the images.

We found that to ensure realistic results some features of images used to evaluate visual similarity are critical. Specifically, we have observed that *shadows*, *ambient occlusion* and gloss affect visual texture perception in a critical way (Figure 4.10), as a texture comprises many small elements that cast shadows over the surface. For this reason, we must opt for a rendering pipeline supporting these features to generate views of the texture, rather than, e.g., approximating the texture image with the dot products of the normal with the light direction.



Figure 4.10: A texture heightmap rendered with (center) or without (right) shadowing and ambient occlusion. Shadowing in small regions of lowered height is critical to a texture's visual appearance.



Figure 4.11: Plot showing render DSSIM and L2 difference errors for a set of textures in optimization steps.

As discussed in Section 4.2, a variety of measures of visual similarity exist and are widely used. Most could be used in our context in a way similar to the function V above used for roughness; e.g., Zhang et al. (2018) describes a perceptual measure of visual similarity represented with a neural network, that can be easily applied in our context. However, we found that in the optimization context, these measures tend to be too "permissive": while these metrics are good for measuring distance between real images, synthetic images can be far from a given image perceptually, but close in the sense of these metrics. For this reason, we opt for a relatively conservative  $L_2$  norm of the difference between images. Figure 4.11 shows a scatter plot exhibiting that L2 has a correlation with DSSIM.



Figure 4.12: Two examples from the test set for visual rendering. The learned function for the rendering of heightmaps was learned with high accuracy: in most cases generated and real renderings are visually indistinguishable.

**Rendering.** Heightmaps were rendered in a gray material with low specularity, similar to matte plastic, using a Phong shader. Objects were rendered with three different lighting conditions, with a single constant-direction parallel-ray light sources at an angle of 35 degrees from the x-y plane and rotated on the z-axis 10, 130, or 250 degrees. Images were rendered at  $128 \times 128$  px using Blender.

While differentiable renders have recently appeared Li et al. (2018), given the highly restricted nature of the renderings that we need to compute (square texture samples), we opted for a similar approach as we use for the stress maps for the roughness measure. This approach also provides a gradient of the rendered image with respect to the heightfield as an additional benefit.

For each lighting condition, we train the generative adversarial network in Isola et al. (2017) on a set of 4764 images, with a validation set of size 1059. The network was trained for 200 iterations. Results showed high accuracy, as seen in Figures 4.12 and 4.13. All three lighting conditions had similarly high accuracy (with mean pixel errors of 2.2%, 2.3%, and 2.4%).

The neural network offers a significant speedup to rendering: the neural network render computation time is only 0.05 seconds after the network is loaded; while traditional rendering



Figure 4.13: Left: L1 loss convergence of the generator during training of the GAN on texture rendering for one lighting condition. Right: Histogram of the percent differences of all rendered pixel values across 300 real and generated texture pairs in the test set. Real pixel values are approximated very closely by the network, with most pixels changing by less than 5%. The mean difference is 2.3%.

time is approximately 15 seconds with ray-tracing shadows using Adaptive QMC and 20 samples for the lighting source, and ambient lighting and occlusion.

# 4.5 Results

#### 4.5.1 Optimization results

Figure 4.14 shows the results of altering the roughness of a selection of textures using our optimization for a desired tactile roughness and a maintaining of visual appearance. Textures are rendered here using a different lighting setup than the ones used for learning. Textures shown represent  $10 \times 10 mm^2$  in size.

Choosing a ground truth to compare to in our experiments is somewhat difficult, as we are not aware of any previous work on optimizing tactile properties for complex textures. We have chosen *linear scaling* as one obvious way to change geometry to increase texture roughness, while maintaining similarity to the original texture; this method was suggested in Tymms et al. (2018).

On the righthand side of Figure 4.14, we show the results of using linear scaling of textures

Original Texture	Roughness achieved with optimization			Roughness achieved with linear scaling		
	0.043	0.07	0.12	0.043	0.07	0.12
				172		

Figure 4.14: Seven example textures optimized for a desired roughness. The leftmost column shows the original, target visual texture; the next three columns show the results when the roughness is achieved through our optimization process; the final three columns show the results when the same roughness is achieved through linear scaling in the z and/or xy directions. The optimization process achieves the desired roughness with nearly-imperceptible changes to the visual appearance.

to achieve the desired roughness. Textures are first scaled in height up to a limit of 3 mm; then, if necessary, they are scaled in the x-y direction. The optimization-generated textures are nearly indistinguishable from the original textures, while the textures modified with linear scaling are almost always noticeably different, except in cases where the desired roughness is very close to the original roughness. Making the texture flatter or scaling it upwards results in obvious differences. Additionally, for some textures, a sufficient change in roughness is not achievable through linear scaling alone.

#### 4.5.1.1 Errors

**Roughness** To ensure that the learned functions were robust to the types of textures generated with optimization, the errors in computed roughness were also computed for a set of 150 optimized textures, with three different target roughnesses. The average error between the simulated and learning-computed roughness for the optimized texture was 8.4% with a median of 6.4%, compared to an average of 8.0% and mean of 5.3% for the overall test set.

**Contact area** The same test was performed for a set of 100 textures optimized to have significantly different target contact area. Here the average error in contact area between the simulation and the learned data was 9% with a median of 4.1%. The average error for the non-optimized input set was 7.9%, with a median of 2.4%.

## 4.5.2 Evaluation and comparisons

The relationship between a surface's geometry and its tactile properties is intricate, as it depends on the difficult-to-predict way the elastic skin contacts the texture geometry. The tactile roughness is dependent on the uneven distribution of pressure resulting from that contact area. Optimization for these tactile properties while maintaining a similar appearance results in subtle changes to the texture geometry, as shown in Figure 4.16. It typically is not



Figure 4.15: Renderings of two textures optimized for different contact areas.



Figure 4.16: Example of a texture cross-section for textures optimized for roughness. Changes to peaks and troughs are not easily predictable.

as simple as, for example, using height modification or frequency filtering: the target may be impossible to achieve, and the visual appearance may not be preserved well, as discussed below.

#### 4.5.2.1 Comparison with other methods

**Height modification** A simple method of altering a texture's roughness or contact area is to vertically scale the texture. This method was suggested to alter texture roughness in Tymms et al. (2018). If a texture is scaled up vertically, the contact area will decrease and the roughness will increase; the relative geometry is preserved, which might suggest that the appearance is also preserved to an extent. However, as seen in Figures 4.17 and



Figure 4.17: Comparison of optimizing a texture to change contact area or scaling it to change contact area. The optimization results in smaller changes to the geometry and better preservation of visual appearance.

4.14, the appearance is often not preserved when using scaling. The contact and roughness optimizations alter the geometry in precise and small ways to change the contact while preserving appearance.

**Frequency modification** Another intuitive method of altering a texture's roughness is to use bandpass filtering, altering the texture in the frequency domain to reduce or amplify certain frequencies. Literature and psychophysics studies suggest that roughness perception is highest when features are spaced at a wavelength of 2-3 mm apart Hollins and Bensmaïa (2007).

However, we have observed that modifying a texture to alter the frequencies in that range does not alter the roughness is a reliable manner for all textures. For example, if the frequency



Figure 4.18: Comparison of modifying a texture's roughness by modifying the dominant frequency of the texture, and using the optimization process. Modifying the frequency adds large-scale noise to the geometry, which is clearly visible on the texture.

is increased but the amplified areas are not contacted by the skin, the roughness will not be affected. More importantly, modifying the frequencies does not guarantee preservation of visual appearance. Figure 4.18 shows an example of modifying a texture's roughness by 4 JND by increasing the geometry's frequencies in the 2.5mm wavelength range. The large-scale noise added to the geometry to achieve the target roughness is visible in the texture. Our optimization produces smaller changes in the geometry that are not easily apparent.

**Other filtering methods** Contact area and tactile roughness depend on the way the elastic skin conforms around the geometry, which changes in nontrivial ways when the geometry is e.g. smoothed using a filter. For example, smoothing a sharp peak results in increased contact area and decreased height, which decreases roughness; but smoothing a round peak results in decreased contact area and therefore may increase perceived roughness.

## 4.5.3 Visual Experiments

In a set of human visual experiments, we tested the accuracy of our visual optimization by comparing the source texture appearance to the optimized texture appearance and to a version of the texture scaled linearly to achieve the same roughness.



Figure 4.19: Heightmaps of the six textures used in visual experiments.

#### 4.5.3.1 Stimuli

Six source textures were chosen to test (shown in Figure 4.19). Source textures comprised different types of possible natural and manufactured textures and had different base tactile roughness values.

For each source texture, four target roughness values were selected in the same space, and textures were optimized to achieve those four roughness values. Additionally, successive linear scaling was used to create textures with the same four target roughness values.

For each source textures, a set of eleven 25mm square textured stimuli plates were 3Dprinted using a B9Creator DLP stereolithography printer, at  $50\mu$ m resolution. Three of the textures were derived from different patches of the source textures; four were the optimized textures; and four were linearly scaled textures.

As we have used B9 Black resin to yield the most accurate geometric results, to improve visibility, textures were spray-painted with matte gray primer (Rust-Oleum Flat Gray Primer) and a coat of clear matte varnish.



Figure 4.20: The experimental setup for visual experiments, which allows the subject to comfortably view the three trial textures from an overhead view.

#### 4.5.3.2 Experiments

In each trial, two textures were placed in a case that slides beneath a circular window, through which one of the textures could be seen. Observers viewed the textures overhead at a distance of 40 cm, viewing through a mirror placed at an angle of 45 degrees as seen in Figure 4.20.

During each trial, observers were presented with two different textured surfaces sequentially. One of the pair was derived from the original source texture, and the other could be either another patch of the source texture; a version scaled to a different roughness using linear scaling; or a version scaled to a different roughness using our optimization process. Observers were tasked to choose whether the two textures appeared the same (i.e., derived from the same texture source) or different. Locations of the pair of textures were switched with equal probability. Observers were given 4 seconds to view the textures two times each.

Trials were presented in a pseudorandom ordering, with the constraint that trials using the same source texture were separated by at least two trials.

Six subjects took part in the experiments and performed four repetitions per texture pair. Experiments took place in an office setting with ambient fluorescent lighting. **Experiment results.** The results of the experiments showed that our optimization process performed substantially better than linear scaling. Figure 4.21 shows the proportions for the 48 test textures. The dotted black line on each graph shows the threshold at which subjects judged the reference textures from the same patch as similar to each other. Of the 24 optimized textures tested, 20 of them were judged the same as the source at least 50% of the time. In contrast, only 4 of the linearly scaled textures were judged the same as the source at least 50% of the time. In fact, half of the linearly scaled textures were judged different from the reference textures over 90% of the time throughout all trials. 23 of 24 of the optimized textures were judged more similar than the non-optimized version. The other one was derived from T1, a texture which was had high sensitivity to small changes, as shown by the fact that only 50% of textures from the same source were judged the same.

The bottom panel of Figure 4.21 shows textures accumulated by just-noticeable-difference (JND) threshold distance from the reference texture. In all cases, the optimized textures match the references better than the linearly scaled textures. In general, linear scaling tends to perform more successfully for small decreases in roughness, but performs poorly for larger decreases or increases in roughness. Optimization creates textures that appear very similar for small differences in roughness; the visual difference is only visible when the target roughness is much larger.

#### 4.5.4 Contact area experiments

Twelve textures were fabricated to experimentally verify the change in contact area. For each texture, three versions were fabricated: the original texture, a texture optimized to have 70% the contact area, and a texture optimized to 140% the contact area. These 36 textures were fabricated as 10mm squares, using B9Creator V1.2 with a resolution of  $50\mu m$  in B9 black resin.



Figure 4.21: Top panel: Results from the experiments for each of our six textures. Bottom panel: Proportions for all textures accumulated by JND distance from the reference texture. The x-axis for each graph shows the distance in just-noticeable-differences in roughnesses between the test texture and the reference, and the y-axis shows the proportion judged the same. The dotted black line shows the reference threshold at which subjects judged the reference textures the same as each other.



Figure 4.22: The results of one texture optimized for a lower (top) or higher (bottom) contact area. From left to right: texture rendering, texture fingerprint, thresholded finger contact, and simulated contact.



Figure 4.23: Comparison of the experimental and simulated contact area of 36 textures.

To compute the contact area, the fabricated texture surfaces were coated in ink using a compliant sponge and an ink-pad. The thumb or second finger of a human subject was covered with Tegaderm (3M), a thin layer of transparent plastic with a thickness of 0.1mm. The tegaderm was used to avoid discrepancies due to the fingerprint ridges, and to provide easier cleaning of the finger surface between trials to avoid ink residue. The finger was pressed against the texture with a weight of 8.8 N placed on the finger to ensure uniform force. Then the finger was pressed to a sheet of paper to derive an inkprint of the contact surface.

Nine subjects provided texture finger prints in this manner. The prints were scanned at



Figure 4.24: Photograph of sets of bronze-cast textures used for tactile temperature experiments (T3 and T5). Textures are ordered from less to more contact area. Inconsistencies in appearance may be due to the manufacturing process and polishing.

600dpi in 8-bit grayscale, and the contact areas were computed and averaged over all subjects. The pipeline is shown in Figure 4.22. All optimized contact surfaces fell within 20% of their target contact area, with an average difference of 9.2%. Additionally, the contact areas of the 36 printed textures were compared against the simulated contact areas. Figure 4.23, shows the result of this comparison, with a close linear correlation with an approximate slope of 1.

#### 4.5.4.1 Temperature Experiments

An additional set of experiments was used to determine whether the printed textures felt different from one another in tactile temperature.

**Stimuli** The stimuli for this experiment were twelve textures: four base textures (T2, T3, T4, T5) each optimized with three different contact areas differing by 40%. Each texture surface was applied to the top of a flat plate 1.2mm in height. To enable tactile discriminability at room temperature for the purposes of the experiment, texture models were 3D printed and cast in bronze by Shapeways. A photograph is shown in Figure 4.24.

**Setup and protocols** In the experiments, textures placed on a flat cast-iron plate over ice, which maintained a temperature at the top surface of approximately 16 degrees Celsius

as measured by a laser thermometer.

In each trial, a subject was presented with two textures of the same class with different optimized contact area (either 40% smaller or 40% greater, where 40% is approximately the JND threshold for thermal discrimination found by Tiest and Kappers (2009b)). A cover was placed over the experiment area so that subjects could not see the textures.

Subjects were asked to feel the two textures using static pressure with the index finger and to answer which texture felt colder. Subjects were allowed as much time as needed to feel the textures, and were given time between trials to ensure the finger itself was not too cold. Eight subjects participated in experiments.

**Results** Throughout the trials, subjects responded that the texture with more contact area felt colder 83.1% of the time, which suggests that the threshold of discrimination is indeed approximately 40%, as found by previous research. For pairs that differed by two JND, subjects answered that the texture with more contact area felt colder 91% of the time.

## 4.5.5 Example applications

Applying tactile textures to fabricated objects is useful for both aesthetic and practical reasons. As examples, we fabricated several textured 3D models (Figure 4.25).

**Modeling.** Often, one might prefer a particular visual texture for an object but desire a different or more realistic feeling. We manufactured two animal models as examples. First, a starfish model was textured with a relatively smooth shell texture (roughness 0.05). The texture was altered to feel rougher (roughness 0.092), and was applied to produce another, rougher fabricated starfish with the same appearance (shown in Figure 4.1). Similarly, a textured model of a Wood Frog was produced with a keeled wood pattern. The initial texture had a roughness of 0.045, and was modified to produce a smoother texture of roughness 0.03.

This was applied to manufacture a smoother frog with the same appearance (Figure 4.25a).

**Jewelry.** Tactile and visual aesthetics are common to clothing and jewelry that often touches the skin. As an example of a unique jewelry item, a bracelet was fabricated with links having the same texture appearance, but alternating (rougher, then smoother) tactile feelings (Figure 4.25b). Smoother links had a roughness of 0.06, and the rougher links had roughness 0.09.

Accessibility Tactile items and textures are particularly useful for people with visual impairments. Here, we produce a prototype for a dimmer light switch slider. The texture gradient looks the same throughout, but the roughness increases such that it will correspond with the light intensity as the slider is moved (Figure 4.25c).

# 4.6 Conclusion

We have presented an optimization procedure to preserve texture appearance while altering tactile roughness or temperature. We used neural networks to enable computation of tactile roughness, contact area, and visual appearance at speeds several orders of magnitude faster than the standard methods, providing differentiable functions to be used in optimization to enable convergence toward a target appearance and feeling. We used human experiments to demonstrate that our method provides a significant improvement over simple linear scaling in controlling tactile roughness, and we provided several examples of how our procedure can be used to produce interesting and useful textured objects.



Figure 4.25: From left to right: textured models; models colored by roughness; photographs of 3D-printed models. a) Two frogs textured with a tactile wood texture optimized for different roughnesses. b) A bracelet with textured links that have the same visual texture but have alternating roughnesses. c) A procedural texture slider for a light switch, where the tactile roughness corresponds to light intensity.

## 4.6.1 Limitations and Future Work

Our tactile model only applies to a hard material, and it has a minimum feature resolution, so it may require changes when used for different materials, like soft or fine materials. The model is also based on a simulation of a simplified model of human skin, which, while found to be robust, may be improved by a more complex model. Our procedure could be tuned to any simulation field for a different material or more physically complex skin structure, simply by retraining the neural network on a new set of simulation outputs.

Similarly, our procedure describing visual appearance was tuned to the material that we used (diffuse plastic) and may not be directly usable for very different materials, such as more glossy or translucent surfaces. In these cases, our method could be modified to learn the rendered appearance for a particular desired material given a suitable training set. However, as seen in Figure 4.24, our current visual model can still work to preserve visual appearance fairly well even for non-matte materials.

Our model presents a tradeoff between preserving exact visual appearance and allowing a tactile roughness. Very high changes in tactile roughness may not be achievable while fully preserving visual appearance. However, we find that similarly-appearing textures can typically be produced within a range of 3-4 JND thresholds in each direction. Our metric for visual appearance similarity may be a lower bound for perceptual similarity, so a fast perceptually-based method for texture similarity could be incorporated in the optimization and could improve texture generation.

Our model is based on an overhead view with ambient lighting. At severe angles or severe lighting conditions, the differences may be more apparent. Our model could be tuned to a particular lighting condition if that lighting were used in the training set, but in general an optimized texture likely will not appear exactly the same under all lighting and viewing conditions, as some geometric changes will always be present near the surface. When applied



Figure 4.26: Optimized textures applied to a surface with a radius of curvature of 5 mm. The original texture (center) was optimized for a roughness 1 JND lower (left) or 2 JND higher (right).

to a curved surface, texture differences may be more apparent for this reason (Figure 4.26); however, we find that changes are not very apparent for textures with curvatures down to 10 mm radius.

Our model limits texture height to 3mm as a manufacturing constraint. We have observed that due to the limited elasticity of the finger, textures deeper than this are not different tactually from those with the lower-depth truncated to 3mm. However, we could easily optimize a taller texture by optimizing the top 3mm of it, and preserving the remainder.

To aid in the fabrication process, our method could be integrated into a 3D modeling tool to provide precise control of tactile feeling when modeling a textured fabricable object. Using our model and existing models for compliance using compliant microstructures, it would be possible to control three of the four major dimensions of touch: compliance, temperature, and roughness, and to study the unknown interactions between these properties. Creating objects with differing tactile properties as separate from appearance may also be of interest to the fields of neuroscience and neurophysiology in future studies of psychophysics and multi-modal perception.

Finally, our model could also be expanded with other optimization parameters; for example, we could enforce printability constraints depending on the printer used to manufacture a model.

# Chapter 5

# Conclusion

This thesis has presented three works that demonstrate progress toward the goal of bridging the space between 3D modeling and printing and tactile sensory neurophysiology.

In Chapter 2, we describe a psychophysical study in which human subjects discriminate between 3D-printed textures with different texton parameters. We show that bump textures with textons of larger size, smaller spacings, and uniform arrangements are judged smoother, and that surface area provides an approximation to predict the roughness of bump textures. This study shows that 3D printing can be used to create fine textures to serve as good stimuli for tactile studies in neurophysiology.

In Chapter 3 we derive a simulated skin strain-based model for tactile roughness, which matches human roughness evaluations with high accuracy. We use human experiments to validate this model, and demonstrate how it can be applied to predict and alter surface roughness to fabricate objects for a variety of purposes.

In Chapter 4 we develop a process to optimize textures for a desired roughness or contact area while preserving the appearance. We use machine learning to speed up the simulation of touch in order to quickly and accurately compute tactile qualities and enable direct control of these qualities in the optimization process while maintaining a close approximation of visual appearance.

# 5.1 Unsolved problems and future work

The work described in this thesis provides a groundwork for using 3D printing to control tactile qualities for fabrication or for psychophysics, and it leaves much room for expansion and future work.

The sense of touch is highly complex. A more accurate model of the human finger, including fingerprint ridges, skin layers, and more accurately modeled mechanoreptors, may lead to more accurate simulations and models for human perception. A full model for tactile perception should consider all of the receptors and all four dimensions of touch. Three of these dimensions can be controlled through altering the geometry or material, using our methods for roughness and temperature, and using the existing work of Piovarči et al. (2016) for tactile compliance.

3D-printing technology is currently limited in resolution and is therefore unable to produce surfaces with small-scale roughness, but future technologies may enable more precise control of microgeometry to allow for the study of small-scale roughness as well as friction. Future studies, especially those using active or exploratory touch, could provide insights on how the dimensions interact with each other, and new perceptual models could be created to describe the perception of these qualities during different types of touch.

The tactile models used here could be integrated into a 3D modeling tool to provide quantitative control over tactile feeling when modeling a fabricable object. They could also be combined with additional manufacturing or material constraints to be used for different technologies or materials.

3D-printed tactile objects can be used for a variety of neurophysiological studies. They are precise and controllable in both texture and shape, so they provide affordable custom stimuli that are likely to be useful for many future studies related to touch, mechanoreceptor responses, or manual dexterity.

Finally, an important question that may be addressed in the future with 3D-printed stimuli is how the sense of touch interacts with other senses of the body. For example, it has been shown that tactile illusions can be created by controlling a tactile stimulus at the same time as a visual or audio stimulus. While my work has only considered preserving visual appearance while altering tactile feeling, additional questions exist on how different visual or audio stimuli alter the perceived tactile feeling, and vice versa. These questions are a growing interest for research in haptic technologies, such as tactile touch screens or haptics for virtual reality, in order to explore how to use a limited set of virtual tactile stimuli to enhance the user experience alongside existing visual and audio stimuli.

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