

Psychophysics of Virtual Texture Perception

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Abstract

This thesis describes the creation of an experimental platform for the exploration of human texture perception and its relationship to physical phenomena. Virtual textures are simulated and their physical and psychophysical properties are determined.

Experiments were conducted into the ways in which modeling both texture and probe geometry influence the perception of virtual surfaces. The effects of compliance and friction on texture perception were also explored. Roughness detection thresholds were documented and their relationship to probe geometry and compliance were examined. A spectral analysis of the force signal demonstrated that force variability characterized roughness and that FA1 neural receptors were the receptors primarily responsible for mediating indirect roughness perception.

Psychophysical studies of texture perception have been hampered by the need for the expensive manufacture of finely textured surfaces. These texture samples provide only discrete levels of experimental variables for study and are time-consuming to present to subjects. Virtual haptic textures provide continuous control of variables and are quick and easy to use. Unfortunately, psychophysical experimental results seem to differ between real and virtual textures.

An algorithm was used which modeled probe and texture geometry to render virtual haptic texture that was perceptually the same as real texture. The texture was created by constraining the haptic device manipulandum to follow a surface dictated by the interaction of the size and shape of the virtual probe and texture elements. Compliance and friction effects were also simulated.

Subject roughness magnitude estimations were used to determine the psychophysical function for roughness. The effect of probe geometry, compliance, and friction on this function and on roughness thresholds was determined. Force and position recordings were correlated with roughness estimates and used to evaluate the physical properties characterizing roughness perception.

This thesis provides significant new insight into the perception of roughness and its relationship to texture geometry, compliance and friction. It also establishes an experimental platform and framework which should expedite future studies of texture perception.

Contents

List of Figures	vii
List of Tables	xix
1 Perception of Virtual Textures	1
1.1 Introduction	1
1.1.1 Motivation	1
1.1.2 Problem Description	5
1.2 Background and Previous Work	6
1.2.1 Psychophysics	6
1.2.2 The Psychophysics of Texture Perception	10
1.2.3 Texture Rendering	20
1.3 Approach	25
1.4 Contributions	27
2 Experimental Setup and Design	29
2.1 Magnetic Levitation Haptics	29
2.2 Texture Simulation using the Constraint Surface Algorithm	32
2.3 Roughness Magnitude Estimation	35
2.3.1 Experimental Setup	35
2.3.2 Determining the Psychophysical Function	37
2.3.3 Measurement of Physical Properties Associated with Roughness	39
2.4 JND for Roughness	39
3 Sinusoidal Textures and Point-Probes	45
3.1 Introduction	45
3.2 Experimental Design	47

3.3	Sinusoidal Texture and Roughness Perception	49
3.4	Physical Properties Underlying Roughness Perception	59
3.4.1	Velocity and Roughness	59
3.4.2	Kinetic Energy and Roughness	61
3.4.3	Acceleration and Roughness	63
3.4.4	Force and Roughness Perception	65
3.5	Conclusions	78
4	Probe Size Effects with Trapezoidal Grating Textures	81
4.1	Introduction	81
4.2	Spherical Probe and Trapezoidal Grating Constraint Surface Algorithm	82
4.3	Trapezoidal Grating Experimental Design	88
4.4	Trapezoidal Gratings and Roughness Perception	89
4.5	Trapezoidal Gratings and the Physics of Roughness Perception	98
4.6	Conclusions	111
5	Dithered Conical Textures and Probe Size Effects	117
5.1	Introduction	117
5.2	The Constraint Surface Algorithm for Dithered Conical Textures	120
5.3	Roughness Magnitude Estimation Experimental Design	123
5.4	Dithered Conical Textures and Roughness Perception	125
5.5	Dithered Conical Textures and the Physics of Roughness Perception	132
5.6	JND for Roughness with Dithered Conical Textures	138
5.7	Conclusions	144
6	Dithered Conical Textures and Probe Shape	147
6.1	Introduction	147
6.2	The Constraint Surface Algorithm for Cone-shaped Probes	148
6.3	Roughness Magnitude Estimation Experimental Design	152
6.4	Roughness Perception and the Effects of Probe Shape	154
6.5	Probe Shape and the Physics of Roughness	158
6.6	Probe Shape and the JND for Roughness	164

6.7	Conclusions	166
7	Dithered Conical Textures and Compliance Effects	169
7.1	Introduction	169
7.2	The Penalty Method and Compliance	170
7.3	Roughness Magnitude Estimation Experimental Design	171
7.4	Compliance Effects and Roughness	173
7.5	Compliance Effects and the Physics of Roughness Perception	178
7.6	Compliance and the JND for Roughness	185
7.7	Conclusions	187
8	Texture Perception and the Effects of Friction	189
8.1	Introduction	189
8.2	Virtual Friction Models	190
8.3	Friction and Roughness: Experimental Design	193
8.4	Friction effects on Roughness Perception	195
8.5	Friction and the Physics of Roughness	200
8.6	Conclusions	208
9	Conclusions and Contributions	211
9.1	Roughness Perception with Virtual Probes	211
9.1.1	Roughness and Probe Size	211
9.1.2	Roughness and Probe Shape	214
9.1.3	Confounding Factors in Roughness Perception: Compliance and Friction	216
9.2	The Physical Property Characterizing Roughness	218
9.2.1	Texture's Physical Properties and Neuroreceptors	219
9.3	JND for Roughness with Virtual Textures	220
9.4	Contributions	223
9.5	Future Work	225
	Acknowledgments	229
	Appendices	231

A	Data Fitting Equations, Fit Parameters and Statistical Analysis Tables for Selected Experiments	233
A.1	Sinusoidal Grating Texture	233
A.2	Trapezoidal Grating Texture	233
A.2.1	Psychophysical Functions for Roughness	233
A.2.2	Physical Parameter Functions	235
A.3	Dithered Cone Texture with Spherical Probes	240
A.3.1	Psychophysical Functions for Roughness	240
A.3.2	Physical Parameter Functions	240
A.4	Dithered Cone Texture with Conical Probes	242
A.4.1	Psychophysical Functions for Roughness	242
A.4.2	Physical Parameter Functions	242
A.5	Dithered Cone Texture and Compliance	242
A.5.1	Psychophysical Functions for Roughness	242
A.5.2	Physical Parameter Functions	244
A.6	Dithered Cone Texture with Friction	245
A.6.1	Psychophysical Functions for Roughness	245
A.6.2	Physical Parameter Functions	245
B	Experimental Details	247
B.1	Roughness Magnitude Estimation Experiments	247
B.1.1	Sinusoidal Textures with Point-Probes	247
B.1.2	Trapezoidal Textures with Spherical Probes	248
B.1.3	Dithered Conical Textures with Spherical Probes	248
B.1.4	Dithered Conical Textures with Conical Probes	249
B.1.5	Dithered Conical Textures and Compliance	250
B.1.6	Dithered Conical Textures and Friction	251
	References	253

List of Figures

1.1	Transmission of texture information from physical world to the brain.	3
1.2	Determining JND using unforced weighted up-down adaptive threshold estimation.	8
1.3	Skin touch receptors.(after Valbo and Johansson [142].)	12
1.4	The effect of decreasing texture frequency on probe motion amplitude.	16
1.5	Two dimensional spherical probe tip with a.) square grating and b.) trapezoidal grating. (after “Perceiving roughness via a rigid probe: Effects of probe and surface geometry and exploratory factors,” Klatzky <i>et al.</i>) [66].	17
1.6	A PHANTOM TM Premium 1.0 device. (Image from Sensable Technologies) . . .	17
2.1	a.) Lorentz magnetic levitation device cut-away view of design. b.) Magnetic levitation device used as haptic interface to a virtual world	30
2.2	Screen shot of graphical interface for texture and friction prototyping.	31
2.3	a.) Texture acquisition with surface profilometry measurements using the IBM Magic Wrist. b.) Surface details of American quarter obtained with Magic Wrist texture acquisition system.	32
2.4	a). IBM Magic Wrist b). IBM Magic Wrist mounted on PUMA 560 arm	33
2.5	Flowchart for generalized constraint surface texture algorithm.	34
2.6	Using the drop point to decide base texture spacing. If the comparison texture spacing is larger than the drop point (light-colored zone) a runaway JND may occur.	40
2.7	Determining JND using unforced weighted up-down adaptive threshold estimation. JND determinations for five base texture spacings are shown. The track for a base texture spacing of 1.00 mm may represent a runaway JND.	41
2.8	a.) Subject using the magnetic levitation haptic device during JND experiments. b.) JND experiment subject panel with selection buttons and visual active panel display.	42

3.1	Graphic representation of four examples of sinusoidal grating texture used for psychophysical experiments with a (a). 6mm period, (b) 2 mm period, (c) 0.50 mm grating and (d) 0.25 mm grating.	46
3.2	Plot of individual normalized roughness psychophysical functions for 27 subjects superimposed on their cross subject mean. There is a significant effect of spacing on roughness estimates ($F(32,726)=11.5273$, $p < 0.0001$).	48
3.3	Log plot of the of individual normalized roughness psychophysical functions for 27 subjects superimposed with the log of their cross subject mean.	49
3.4	Magnetic levitation haptic device manipulandum position during a single roughness magnitude estimation trial using a sinusoidal grating with a 0.4 mm peak-to-peak amplitude and a 4 mm spatial period. The trial is approximately 2.2 seconds in duration	51
3.5	Representative example of manipulandum motion along x , y and z axes during a single subject trial on sinusoidal grating texture with a period of a.) 0.025 mm. b.) 1.5 mm, c.) 2.5 mm and d.) 6.0 mm.	52
3.6	Representative example from a single subject of z -axis motion for periods ranging from 0.05 mm to 6.0 mm.	54
3.7	The mean over all subjects of the standard deviation of z -axis position (power) as a function of sinusoidal grating period. A one-way ANOVA shows no significant effect of spacing on power. A third order fit to the data with $R^2 = 0.76$ is also shown.	55
3.8	Cross subject mean trial velocity as a function of sinusoidal grating period with linear fits for x , y , and z axes.	56
3.9	Mean angular velocity for roll, pitch and yaw in radians/second. A linear fit is plotted to each set of data. There is a no significant effect of sinusoid period on roll, pitch or yaw angular velocity.	57
3.10	(a). Semilog plot of temporal frequency (mean over subjects) encountered by subjects versus sinusoidal grating period. Temporal frequency is calculated as a subject's mean x -axis velocity divided by the sinusoidal grating period. (b). Log-log plot of temporal frequency encountered by subjects versus sinusoidal grating period with first order fit. Slope $= -0.977 \pm 0.008$, Y-intercept $= 1.372 \pm 0.051$, $R^2 = 0.99$	58

3.11	Cross subject mean trial velocity and normalized subject roughness estimates as a function of sinusoidal grating periods. A third order fit to each complete data set is shown. ($R^2=0.97$ and 0.95 for roughness and velocity respectively). A linear fit to the data is also shown for small periods of 0.025-1.00 mm and for large periods of 2.25-6.0 mm. (Ascending Roughness Fit $R^2 = 0.80$, Ascending Velocity Fit $R^2 = 0.87$, Descending Roughness Fit $R^2 = 0.9599$, Descending Velocity Fit $R^2 = 0.99$.)	61
3.12	Mean z -axis kinetic energy compared to roughness as a function of sinusoid period. Energy and roughness are normalized for comparison. A third order fit to each data set is shown with $R^2 = 0.99$ for the kinetic energy and $R^2 = 0.97$ for roughness. A linear fit to the data is also shown for small periods of 0.025-1.00 mm and for large periods of 2.25-6.0 mm. (Ascending Roughness Fit $R^2 = 0.80$, Ascending Velocity Fit $R^2 = 0.93$, Descending Roughness Fit $R^2 = 0.96$, Descending Velocity Fit $R^2 = 0.98$.)	62
3.13	Mean z -axis force compared to roughness as a function of sinusoid period. Force and roughness are normalized for comparison. A third order fit to each data set is shown with $R^2 = 0.70$ for force and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows no effect of sinusoid period on mean z -axis forces ($F(32,726)=0.049$, $p=> 0.05$).	63
3.14	Mean z -axis acceleration compared to roughness as a function of sinusoid period. Acceleration and roughness are normalized for comparison. A third order fit to each data set is shown with $R^2 = 0.94$ for acceleration and $R^2 = 0.97$ for roughness. A linear fit to the data is also shown for small periods of 0.025-0.3 mm and for large periods of 1.0-6.0 mm. (Ascending Roughness Fit $R^2 = 0.85$, Ascending Acceleration Fit $R^2 = 0.93$, Descending Roughness Fit $R^2 = 0.97$, Descending Acceleration Fit $R^2 = 0.97$.)	64
3.15	Mean of z -axis force over time during trials at a range of different sinusoid periods. Each line represents individual subject mean z -axis forces over the range of periods. The average over subjects of the mean z -axis force at each period is also shown. There is no significant effect of spacing on the mean absolute z -axis force.	65
3.16	The z -axis force signal power spectral density periodograms for sinusoidal texture periods of 0.025-5.75 mm. Each periodogram is found using a 1024 sample Fast Fourier Transform. The mean of the PSD periodograms over subjects and trial iterations is shown for frequencies from 5-100 Hz.	66

- 3.17 Total power of z -axis force signal from the power spectral density compared to roughness as a function of sinusoid period. Power and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum of 1.39 mm_{period} and $R^2 = 0.98$ for force power and a maximum of 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on power in the z -axis force signal ($F(32,726)=7.5761$, $p= 0.00$). A linear fit to the initial ($< 1.0 \text{ mm texture period}$) and final ($> 1.0 \text{ mm texture period}$) portions of each curve with slopes as follows: Ascending Power= $1.76 \text{ N/mm}_{period}$, $R^2 = 0.83$, Ascending Roughness= 1.38 , $R^2 = 0.80$, Descending Power= $-0.98 \text{ N/mm}_{period}$, $R^2 = 0.97$, Descending Roughness= -0.78 , $R^2 = 0.97$. 68
- 3.18 Roughness estimation function compared with the frequency at which the maximum z -axis force signal, as measured by the power spectral density, is found. Frequency and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum at 1.88 mm_{period} and $R^2 = 0.89$ for frequency and a maximum at 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on the maximum frequency of the z -axis force signal ($F(32,726)=4.2232$, $p= 0.00$). A linear fit to the initial ($< 1.0 \text{ mm texture period}$) and final ($> 1.75 \text{ mm texture period}$) portions of each curve with slopes as follows: Initial frequency= $4.28 \text{ Hz/mm}_{period}$, $R^2 = 0.63$, Initial Roughness= 2.38 , $R^2 = 0.80$, Final frequency= $-1.45 \text{ N/mm}_{period}$, $R^2 = 0.96$, Final Roughness= -1.42 , $R^2 = 0.97$. Outliers greater than 10x the mean over subjects were removed from the frequency data. 69
- 3.19 Roughness function compared with the maximum z -axis force signal, as measured by the power spectral density. Maximum force and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum at 2.45 mm_{period} and $R^2 = 0.93$ for frequency and a maximum at 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on maximum z -axis force signal power ($F(32,726)=3.1514$, $p< 0.001$). A linear fit to the initial ($< 1.0 \text{ mm texture period}$) and final ($> 2.00 \text{ mm texture period}$) portions of each curve with slopes as follows: Initial PSD= $2.29 \text{ N/mm}_{period}$, $R^2=0.86$, Initial Roughness= 1.05 , $R^2 = 0.80$, Final PSD= $-0.61 \text{ N/mm}_{period}$, $R^2 = 0.91$, Final Roughness= -0.62 , $R^2 = 0.97$. Outliers greater than 10x the mean over subjects were removed from the PSD data. 70

3.20	Power Spectral Density of z -axis forces within the FA1 receptor frequency range (5-50 Hz), compared to roughness as a function of sinusoid period. PSD and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum of 0.94 mm_{period} and $R^2 = 0.97$ for PSD and a maximum of 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on FA1 z -axis force signal power ($F(32,726)=7.7873$, $p < 0.001$). A linear fit to the ascending ($< 1.0 \text{ mm texture period}$) and descending ($> 1.5 \text{ mm texture period}$) portions of each curve with slopes as follows: Ascending PSD= $4.12 \text{ N/mm}_{period}$, $R^2 = 0.93$, Ascending Roughness= 1.29 , $R^2 = 0.80$, Descending PSD= $-1.17 \text{ N/mm}_{period}$, $R^2 = 0.97$, Descending Roughness= -0.76 , $R^2 = 0.97$	71
3.21	Power Spectral Density of z -axis forces within the FA2 receptor frequency range (50-500 Hz), compared to roughness as a function of sinusoid period. PSD and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum at $0.025 \text{ mm}_{period}$ and $R^2 = 0.99$ for PSD and a maximum at 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on FA2 z -axis force signal power ($F(32,726)=77.6155$, $p = 0.00$). A linear fit to the initial ($< 1.0 \text{ mm texture period}$) and final ($> 1.0 \text{ mm texture period}$) portions of each curve with slopes as follows: Initial PSD= $-5.77 \text{ N/mm}_{period}$, $R^2 = 0.96$, Initial Roughness= 0.80 , $R^2 = 0.80$, Final PSD= $-0.49 \text{ N/mm}_{period}$, $R^2 = 0.52$, Final Roughness= -0.61 , $R^2 = 0.97$	72
3.22	Power Spectral Density of z -axis forces within the FA1 receptor frequency range (5-50 Hz) divided by PSD for FA2 receptor frequency range (50-500 Hz) as a function of sinusoid period. This ratio indicates the relative power of the low frequency force signal to the high frequency force signal.	73
3.23	Correlation coefficient between subjective roughness and the power in the force signal in a 20 Hz window sliding across the PSD periodogram. The window's lower edge is at the frequency displayed on the x axis. The FA1 and FA2 frequency bandwidths are indicated with arrows.	74
3.24	Correlation coefficient between subjective roughness and the power in the force signal in a frequency window of increasing size. The window's lower frequency is fixed at 5 Hz. The correlation coefficient is plotted against the the window's upper frequency which is used as the independent variable. The FA1 and FA2 frequency bandwidths are indicated with arrows.	75

3.25	Correlation coefficient between subjective roughness and the power in the force signal for small period (0.025-0.5 mm) sinusoidal textures in a frequency window of increasing size. The window's lower frequency is fixed at 5 Hz. The correlation coefficient is plotted against the the window's upper frequency which is used as the independent variable. The p-value of the correlation coefficient is also shown.	76
3.26	Correlation coefficient between subjective roughness and the power in the force signal for large period (2.0-6.0 mm) sinusoidal textures in a frequency window of increasing size. The window's lower frequency is fixed at 5 Hz. The correlation coefficient is plotted against the the window's upper frequency which is used as the independent variable. The p-value of the correlation coefficient is also shown.	77
4.1	Graphic representation of four examples of trapezoidal grating texture used for psychophysical experiments with a (a). 0.96 mm period, (b) 1.96 mm period, (c) 3.46 mm grating and (d) 5.96 mm grating.. . . .	82
4.2	Cross-section of trapezoidal grating texture with dimensions.	83
4.3	Cross-section of trapezoidal grating texture with inflection points. a) Small probe. b) Larger Probe. c) Very Large Probe.	84
4.4	Trapezoidal grating roughness functions for 4 different probe sizes. Individual subject functions are shown as thin lines while the mean function for each probe size is shown as a thick line.	90
4.5	Semilog plot of second order fit to mean log normalized roughness estimates of trapezoidal grating textures with various spacings explored with spherical probes of 0.25, 0.5, 1.0 and 1.5 mm radius. Vertical lines indicate maxima (Drop Points).	91
4.6	Semilog plot of third order fit to mean log normalized roughness estimates of trapezoidal grating textures with various spacings explored with spherical probes of 0.25, 0.5, 1.0 and 1.5 mm radius. Vertical lines indicate maxima (Drop Points).	92
4.7	a) Penetration depth, P_d , is calculated from the radius of the probe, r_{probe} , and the separation of the elements, el_{sep} for rectangular texture elements. The drop point in this case occurs when $el_{sep} > r_{probe}$. b) P_d is calculated from the r_{probe} , el_{sep} and element side angle α for conical or trapezoidal texture elements. The drop point is the point at which P_d is equal to element height, el_h	93

4.8	Unconstrained nonlinear optimization fit of logistic curve to roughness magnitude estimation data. Vertical lines indicate 80% of height of each curve. Sum of squared errors are 0.013, 0.004, 0.004, and 0.002 for each fit curve respectively. The fitted logistic curve was of the form $y = C + \frac{A}{1+e^{-\lambda(x-B)}}$. Values of A , B , C , and λ may be found in appendix A .	94
4.9	Drop point (DP) error explained by probe velocity and geometric model. In a) and b) when velocity is 0, DP is determined only by geometry. In c) with velocity greater than 0, DP is determined by probe velocity and geometry.	95
4.10	Plot of the mean velocity versus texture period for 3 axes. Texture period and probe size show no significant effect on x - and y -axis velocity. Z -axis velocity is significantly affected by both period and probe size.	97
4.11	Representative example of manipulandum motion along x , y and z axes during a single subject trial on trapezoidal grating texture with a period of 3.96 mm for spherical probe radii of a) 0.25 mm b) 0.50 mm c) 1.0 mm and d) 1.5 mm.	99
4.12	Representative trapezoidal grating texture z -axis position samples for four probe sizes covering the full range of texture periods.	100
4.13	Plot of the average over subjects of the standard deviation of the z -axis position signal versus element spacing. A third order fit to the standard deviation data is shown. A third order fit to subject roughness estimates is also shown for comparison. Maxima in the standard deviation fits are shown as vertical lines.	101
4.14	Plot of the mean z -axis velocity for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the velocity data and fitted with 3rd order curves are shown as light gray lines.	103
4.15	Plot of the mean z -axis kinetic energy for trapezoidal grating texture at various texture periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the kinetic energy data and fitted with 3rd order curves are shown as light gray lines.	105
4.16	Plot of the mean z -axis acceleration for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the acceleration data and fitted with 3rd order curves are shown as light gray lines.	106

4.17	Plot of the mean over subjects of the z -axis force for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data. Roughness estimates, normalized to the force data and fitted with 3rd order curves are shown as light gray lines.	108
4.18	Plot of the total z -axis force signal power for trapezoidal grating texture at various periods. The power is the integral of the periodogram of the z -axis force. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the force signal power data and fitted with 3rd order curves are shown as light gray lines.	109
4.19	Plot of the z -axis force signal power in FA1 band (5-50 Hz) for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the force signal power data and fitted with 3rd order curves are shown as light gray lines.	111
4.20	Plot of the z -axis force signal power in FA2 band (50-500 Hz) for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the force signal power data and fitted with 3rd order curves are shown as light gray lines.	112
5.1	Graphical representation of the range of dithered conical texture models for investigation of probe size effects. Textures have element spacings ranging from 0.5 to 5.5 mm and probe radii ranging from 0.25 to 1.5 mm. a) Probe Size = 1.5 mm, Spacing = 0.5 mm, b) Probe Size = 1.5 mm, Spacing = 5.5 mm, c) Probe Size = 0.25 mm, Spacing = 0.5 mm, d) Probe Size = 0.25 mm, Spacing = 5.5 mm.	118
5.2	Scanning electron micrographs of dithered conical texture plates used in Klatzky <i>et al.</i> 's psychophysical experiments [66]. a) Dithered field of conical elements. b) Close-up of single conical element.	119
5.3	a) Large spherical probe moving over a smaller cone where first contact occurs at the cone's upper lip. The critical height of contact, h_{crit} , based on the probe radius and angle of the cone, is equal to the cone height, C_h . b) Smaller spherical probe moving over a larger cone where first contact occurs below the cone's upper lip ($h_{crit} < C_h$).	121

5.4	a.) Second order fit to mean normalized roughness estimates of dithered conical textures at 11 spacings explored with spherical probes. b.) Third order fit to mean normalized roughness estimates of dithered conical texture at 11 spacings explored with spherical probes.	127
5.5	Thin lines represent individual subject roughness estimates fitted with 2nd order curves in a log-log plot. The 2nd order fit to the mean data is plotted as a thick line. Each plot represents a single probe radius as follows: a) 0.25 mm b) 0.50 mm c) 1.0 mm and d) 1.5 mm.	128
5.6	Comparison of the curvature and maxima location (drop points) of the psychophysical function for roughness ($\Psi(I)$) for real and virtual spherical probes on dithered conical textures. Real data are taken from Klatzky <i>et al.</i> [66].	130
5.7	Representative example of manipulandum motion along x -, y - and z -axis during a single subject trial on dithered conical textures with a period of 3.50 mm for spherical probe radii of a) 0.25 mm b) 0.50 mm c) 1.0 mm and d) 1.5 mm. Subject was a right-handed male. . .	133
5.8	Representative samples of z -axis position for the range of probe sizes (0.25-1.5 mm) and texture spacings (0.5-5.5 mm) used in the dithered conical texture probe size experiments. .	134
5.9	Dithered conical texture probe size experiment mean z -axis velocity versus texture period for four different probe sizes. Light lines indicate the roughness estimates for the same probe sizes and texture periods.	136
5.10	Second order fit to the total power in the z -axis force signal versus plotted against texture period for four probe sizes. Vertical lines indicate the location of the fit maxima and thin gray lines indicate subject roughness perception normalized to respective total power curves.	138
5.11	Threshold of the change in spacing that results in a JND in roughness for three different probe radii measured at a variety of base spacings.	141
5.12	The relation of JND to probe size for similar base texture spacings (by quintile).	143
6.1	Constraint surface algorithm for probes with conical shape. Three conditions exist which depend on the relationship between probe height, h_{probe} , the probe's pitch angle, δ and the texture element angle, α : a) $90^\circ - \delta \geq \alpha$, b) $90^\circ - \delta < \alpha$ and $h_{probe} < el_h$, and c) $90^\circ - \delta < \alpha$ and $h_{probe} \geq el_h$	149
6.2	a.) Second order fit to mean normalized roughness estimates of dithered conical textures explored with conical probes of 0.0625 to 1.5 mm radius. Probe height was 0.25 mm b.) Third order fit to the same roughness estimate data.	155

6.3	a.) Second order fit to mean z -axis velocity in a log-log plot for dithered conical textures explored with conical probes of 0.0625 to 1.5 mm radius. Probe height was 0.25 mm b.) Third order fit to the same data. Subject roughness estimates, normalized to velocity, are shown as thin gray lines.	160
6.4	a.) Second order fit to total power in the z -axis force signal in a log-log plot for dithered conical textures explored with conical probes of 0.0625 to 1.5 mm radius. Probe height was 0.25 mm b.) Third order fit to the same data. Subject roughness estimates, normalized to velocity, are shown as thin gray lines.	162
6.5	JND thresholds for conical probes on dithered truncated conical textures. Base spacings vary depending on probe radius.	165
6.6	JND thresholds for base texture spacings by quintile for three conical probe radii.	167
7.1	Second order fit on a log-log plot, to mean texture roughness magnitude estimates for probes of four different compliances. The estimates are normalized over all subjects using the mean estimate over all subject trials.	174
7.2	Mean over all subjects of z -axis position at each element spacing during magnitude estimation with four different levels of compliance. A linear fit is shown.	176
7.3	Mean over all subjects of z -axis force applied at each element spacing during magnitude estimation with four different levels of compliance. A linear fit in the log-log plot is shown.	177
7.4	Representative one second samples of z -axis position recordings (1000 Hz) for four levels of probe compliance across the range of texture element spacings.	179
7.5	Second order fit in a log-log plot to mean z -axis velocity plotted against texture spacing for four levels of compliance. Subject roughness estimates, normalized against z -axis velocity, are shown as thin gray lines for comparison. Vertical lines indicate the maxima of the velocity fits.	181
7.6	Representative one second samples of z -axis force recordings (1000 Hz) for four levels of probe compliance across the range of texture element spacings.	182
7.7	Second order fit to the total power in the z -axis force signal plotted versus texture spacing for four different probe sizes. Subject roughness estimates, normalized to the total power curves, are shown as thin gray lines for comparison.	183
7.8	Just noticeable difference in roughness for changes in element spacing for probes with three different levels of compliance.	186

7.9	Just noticeable difference in roughness versus probe compliance for the same levels of base spacing texture.	187
8.1	Second order fit to mean normalized roughness versus texture spacing for four levels of stick-slip friction (Hayward model).	197
8.2	Second order fit to mean normalized roughness versus texture spacing for two levels of viscous friction.	199
8.3	Second order fit in a log-log plot to total power in the z -axis force signal plotted against texture spacing for four levels of stick-slip friction (Hayward model). Subject roughness estimates, normalized to power, are shown as thin gray lines for comparison.	202
8.4	Second order fit to mean absolute instantaneous z -axis velocity of the haptic probe versus texture spacing for four levels of stick-slip friction (Hayward model). Subject roughness estimates, normalized to velocity, are shown as thin gray lines for comparison.	203
8.5	Second order fit to total power in the z -axis force signal versus texture spacing for two levels of viscous friction. Subject roughness estimates, normalized to power, are shown as thin gray lines for comparison	205
8.6	Second order fit to mean z -axis velocity plotted against texture spacing in a log-log plot for two levels of viscous friction. Subject roughness estimates, normalized to velocity, are shown as thin gray lines for comparison	207
9.1	Comparison of the psychophysical function for roughness, $\Psi(I)$, for a) Sinusoidal gratings explored with a point probe. b) Trapezoidal gratings explored with spherical probes. c) Dithered conical textures explored with spherical probes.	212
9.2	Comparison between spherical and conical probes of the curvature of a second order fit to the psychophysical roughness function for four probe radii on dithered conical textures. Also shown is the location of maximum roughness in terms of element spacing (the drop point) for spherical (2nd order fit) and conical (3rd order fit) probes.	215
9.3	Maximum roughness and absolute curvature of a second order fit to roughness estimates for varying levels of compliance. Curvature is normalized to roughness for display purposes. .	216
9.4	The effects of stick-slip friction (Hayward Model) and viscous friction on the curvature of the psychophysical function for roughness.	217

9.5 Weber fractions for probe size, probe shape and compliance experiments. Dark areas represent the minimum Weber fraction for that probe type while light areas represent the mean over all base textures. Error bars indicate $\pm$ the standard error. 221

List of Tables

1.1	Mechanoreceptor afferent systems and their properties. Adapted from Stevens' Handbook of Experimental Psychology, Chapter 13: The Neural Basis of Haptic Perception [59]. *Frequency range is from Sensation and Perception, 2nd edition [154]	13
3.1	Slope of roughness function in a log-log plot for small sinusoid periods (0.025-1.75 mm) and large sinusoid periods (2.25-6.0 mm).	50
3.2	1-way ANOVA results for effect of sinusoid period on manipulandum linear and angular velocity. Only z -axis velocity shows a significant effect.	60
3.3	Correlation coefficients for various physics parameter functions when compared to the psychophysical roughness function for sinusoidal gratings with periods from 0.025-6.0 mm. Sum of Squares difference is the square of the difference between the parameter function and the roughness function divided by the square of the roughness function for normalization. 78	
4.1	The trapezoidal texture period at which maximum roughness occurs based on 2nd and 3rd order polynomial curves fitted to roughness estimates averaged across subjects as well as the height of a fitted logistic curve (80% of max-min). Curvature of the 2nd order fitted curve (on a log-log plot) and the period of maximum roughness predicted by the geometric model are also shown. Results are shown for four probe sizes.	93
4.2	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to subject roughness estimates.	94
4.3	The trapezoidal grating texture period at which maximum roughness occurs based on 2nd and 3rd order curves fitted to unlogged normalized roughness estimates averaged across subjects. Curvature of the 2nd order fitted curve and the maximum roughness predicted by the geometric model are also shown. Results are shown for four probe sizes	102

4.4	The trapezoidal grating texture period at which maximum standard deviation (σ) occurs based on 2nd and 3rd order curves fitted to STD estimates averaged across subjects. Curvature of the 2nd order fitted curve and the maximum roughness predicted by the geometric model are also shown. Results are shown for four probe sizes.	102
4.5	The trapezoidal texture period at which maximum velocity occurs based on 2nd and 3rd order curves fitted to roughness estimates averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of velocity versus spacing is shown. For comparison, the roughness maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	104
4.6	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to subject velocity estimates.	104
4.7	The trapezoidal texture period at which maximum kinetic energy occurs based on 2nd and 3rd order curves fitted to kinetic energy averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of kinetic energy versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	105
4.8	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to kinetic energy.	106
4.9	The trapezoidal texture period at which maximum acceleration occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of acceleration versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	107
4.10	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to acceleration.	107
4.11	The trapezoidal texture period at which maximum total power in the force signal occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of total power in the force signal versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	110
4.12	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to total power in the force signal.	110

4.13	The trapezoidal texture period at which maximum total power in the force signal FA1 band (5-50 Hz) occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of total power in the force signal FA1 band versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	113
4.14	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to total power in the force signal FA1 band.	113
4.15	The trapezoidal texture period at which maximum total power in the z -axis force signal FA2 band (>50 Hz) occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of total power in the force signal FA2 band versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	114
4.16	Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to total power in the z -axis force signal FA2 band. It should be pointed out that for the third order maxima, if only the smallest three probe sizes are compared, probe size effect is highly significant (2/69, $F=31.7$, $p < 0.0001$).	114
5.1	The maxima of dithered conical texture roughness estimates based on 2nd and 3rd order curves in a log-log plot (antilog values shown). Curvature of the 2nd order fitted curve on a log-log plot of roughness versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	129
5.2	Significance of probe size effects, determined using a 1-way ANOVA on curvature, maximum roughness (curve height) and maxima of a 2nd and 3rd order fit to roughness estimates.	129
5.3	Correlation coefficients for various physical property $\Phi(I)$'s when compared to the roughness $\Psi(I)$ for dithered conical textures. Outliers have been removed from maglev and subject data.	135
5.4	The curvature and element spacing at which the maximum occurs for unlogged second order fits to the dithered conical texture $\Psi(I)$ as well as the curvature and maxima location for similar 2nd order fits to the mean z -axis velocity $\Phi(I)$. Results are shown for four probe sizes.	137
5.5	1-way ANOVA results showing significance of probe size effects on curvature and maxima of an unlogged 2nd order fit to the z -axis velocity and total PSD power $\Phi(I)$'s as well as the roughness psychophysical function $\Psi(I)$	137

5.6	The curvature and element spacing at which the maximum occurs for unlogged second order fits to the dithered conical texture $\Psi(I)$ as well as the curvature and maxima location for similar 2nd order fits to the total z -axis PSD power $\Phi(I)$. Results are shown for four probe sizes.	139
5.7	Probe radius and base texture spacing used for dithered conical texture JND experiments. .	141
5.8	Just noticeable differences for probe radius–base texture pairings.	142
6.1	The maxima of the cone-shaped probe texture roughness functions based on 2nd and 3rd order curves in a log-log plot. Curvature of the 2nd order fit to roughness data and the predicted drop points for five sizes of cone-shaped probe.	156
6.2	Significance of probe radius effects on roughness functions in the cone-shaped probe experiment, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to roughness estimates in a log-log plot. Only the largest four probes were analyzed. . .	157
6.3	Correlation coefficients for the physics function ($\Phi(I)$) of various physics properties when compared to the psychophysical function for roughness ($\Psi(I)$) for the largest four sizes of conical probe. Outliers have been removed from maglev and subject data.	159
6.4	The maxima of z -axis velocity functions based on 2nd and 3rd order fits to data in a log-log plot. Curvature of the 2nd order fit to z -axis velocity plotted against texture period is also shown as well as the predicted maxima. Results are shown for five conical probe radii. . .	161
6.5	Significance of cone-shaped probe radius effects on mean z -axis velocity determined using a 1-way ANOVA on curvature, curve height and maxima location of 2nd and 3rd order fits to velocity data in a log-log plot. Only the largest four probe sizes are used.	161
6.6	The maxima of the total power in the z -axis force signal functions based on 2nd and 3rd order fits in a log-log plot. Curvature and the predicted maxima are also shown for five conical probe radii.	163
6.7	Significance of conical probe radius effects on total power in the z -axis force signal determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit in a log-log plot. Only the four largest probe sizes were used.	163
6.8	Probe radius and base texture spacing used for conical probe JND experiments.	165
6.9	JNDs for conical probe radius–base texture pairings.	166

7.1	The maxima of the dithered conical texture roughness estimate functions based on 2nd and 3rd order curves. Curvature and height of the 2nd order fit to roughness estimates plotted against texture period are also shown. Results are shown for four levels of compliance.	173
7.2	Significance of probe size effects on curvature and maxima of a 2nd and 3rd order fits to roughness data in the compliance experiment, determined using a 1-way ANOVA.	175
7.3	Correlation coefficients for various physics property measures with the psychophysical function for roughness for dithered conical textures with four levels of probe compliance. Outliers have been removed from maglev and subject data.	180
7.4	The maxima of dithered conical texture mean z -axis velocity functions based on 2nd and 3rd order curves. Curvature of the 2nd order fit to roughness estimates plotted against texture spacing is also shown. Results are shown for four levels of compliance.	180
7.5	Significance of probe size effects in the compliance experiment determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to mean z -axis velocity.	181
7.6	The maxima of the dithered conical texture total power in the z -axis force signal based on 2nd and 3rd order fits in a log-log plot. Curvature and height of the 2nd order fit to total power plotted against texture spacing is also shown. Results are shown for four levels of compliance.	184
7.7	Significance of probe size effects in the compliance experiment, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit in a log-log plot to total power in the z -axis force signal.	184
7.8	Just noticeable differences for probe compliance–base texture pairings.	186
8.1	The maxima of roughness functions based on 2nd and 3rd order fits to magnitude estimation data for four levels of the Hayward friction model's k_{Hay} . Curvature and the predicted maxima of the 2nd order fitted curve on the log-log plot are also shown.	197
8.2	Significance of stick-slip friction effects, determined using a 1-way ANOVA, on curvature, curve height and maxima of a 2nd and 3rd order fit to roughness magnitude estimates.	198
8.3	The maxima of the dithered conical texture roughness functions based on 2nd and 3rd order curves in a log-log plot. Curvature of the 2nd order fitted curve on a log-log plot of roughness versus spacing is shown. Results are shown for two levels of viscous friction.	200
8.4	Significance of probe size effects in viscous friction experiment, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to roughness magnitude estimates.	200

8.5	Correlation coefficients for various physical properties when compared to the roughness function, for dithered conical textures with varying levels of Hayward friction. Outliers have been removed from maglev and subject data.	201
8.6	The maxima of 2nd and 3rd order fits to the total power in the z -axis force signal functions in a log-log plot for four levels of the Hayward friction k_{Hay} . Curvature of the 2nd order fitted curve is also shown.	202
8.7	Significance of Hayward friction effects, determined using a 1-way ANOVA on curvature, height, and maxima of 2nd and 3rd order fits to total power in the z -axis force signal. . . .	203
8.8	The maxima of z -axis velocity functions based on 2nd and 3rd order fits to z -axis velocity in a log-log plot. Curvature of the 2nd order fitted curve is also shown. Results are shown for four levels of the Hayward friction model's k_{Hay}	204
8.9	Significance of Hayward friction effects, determined using a 1-way ANOVA on curvature, height and maxima of 2nd and 3rd order fits to z -axis velocity.	204
8.10	The maxima of 2nd and 3rd order fits to total power in the z -axis force signal versus element spacing data for two levels of viscous friction. Curvature of the 2nd order fit is also shown.	205
8.11	Significance of viscous friction effects determined using a 1-way ANOVA on curvature, height and maxima of 2nd and 3rd order fits to the total power in the z -axis force signal.	206
8.12	The maxima of 2nd and 3rd order fits to the the mean z -axis velocity data in a log-log plot for two levels of viscous friction. Curvature of the 2nd order fit is also shown.	206
8.13	Significance of viscous friction effects on the curvature, height and maxima of the 2nd and 3rd order fits to z -axis velocity, determined using a 1-way ANOVA.	207
8.14	Correlation coefficients for various physics properties when compared to the roughness psychophysical function for dithered conical texture with varying levels of viscous friction. Outliers have been removed from maglev and subject data.	208
9.1	Weber fractions for probe size, shape and compliance experiments. Each experiment has 3 probe types. For the size and shape experiments types 1-3 are probe radii of 0.25, 0.50 and 1.0 mm respectively. For the compliance experiment types 1-3 are probes with compliances of 5.0, 10.0, and 15.0 N/mm respectively. The mean Weber fraction over probe types is shown in the last row.	222

9.2	Primary experimental results. The shape of the psychophysical function for each experiment is shown. The effect of experiment factor (increasing probe size, compliance or friction levels) on $\Psi(I)$'s absolute curvature, drop point, and maximum, calculated from a second order fit to experimental data, is shown where applicable. The strength of the correlation of the physical function for z -axis force variability ($\Phi(I)_{Fz}$) with the psychophysical function is presented for all experiments. The minimum JND determined for three experiments is also shown.	224
A.1	Second and third order fits on a log-log plot, to roughness estimation profiles for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	233
A.2	Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to subject roughness estimates for trapezoidal gratings. .	234
A.3	Logistic fits to roughness magnitude estimation on a log-log plot for trapezoidal gratings. Four probe sizes are used. Sum of square errors are shown for individual fits beside their equations.	234
A.4	Second and third order fits on a unlogged plot, to roughness estimation profiles for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	234
A.5	Second and third order fits to z -axis position standard deviation functions for trapezoidal gratings. The functions are based on the cross-subjects averaged standard deviation. Four probe sizes are used. R^2 values for individual fits are shown beside their equations. . . .	235
A.6	Second and third order fits to mean instantaneous velocity data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations. .	235
A.7	Second and third order fits to mean kinetic energy data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	235
A.8	Second and third order fits to mean instantaneous acceleration data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations. .	236
A.9	Second and third order fits to mean z -axis force signal total power data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	236

A.10	Second and third order fits to mean z -axis force signal FA1 band (5-50 Hz) power data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	236
A.11	Second and third order fits to mean z -axis force signal FA2 band (> 50 Hz) power data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	236
A.12	Second and third order fits to mean maximum power in the z -axis force signal for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	237
A.13	The trapezoidal texture period at which the maximum power in the force signal occurs based on 2nd and 3rd order curves fitted to data averaged across subjects. Curvature of the 2nd order fitted curve on an unlogged plot of the maximum power in the force signal versus spacing is shown. For comparison, the roughness maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.	237
A.14	Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the maximum power which occurs in the force signal.	237
A.15	Second and third order fits to frequency at which maximum power in z -axis force signal data occurs for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	238
A.16	The trapezoidal texture period at which the frequency of the maximum power in the force signal occurs based on 2nd and 3rd order curves fitted to data averaged across subjects. Curvature of the 2nd order fitted curve on an unlogged plot of the frequency of the maximum power in the force signal versus spacing is shown. For comparison, the roughness maxima predicted by the geometric model are also shown. Results are shown for four probe sizes. .	238
A.17	Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the frequency at which maximum power occurs in the force signal for trapezoidal gratings.	238
A.18	Correlation coefficients for various physics parameter functions when compared to the roughness psychophysical functions of trapezoidal gratings.	239
A.19	Second and third order fits to mean normalized roughness estimates for dithered cone textures in a log-log plot. Four probe sizes are shown. R^2 values for individual fits are shown beside their equations.	240

A.20	Second and third order fits to mean z -axis velocity for dithered cone gratings in an unlogged plot. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	240
A.21	Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the z -axis velocity.	240
A.22	Second and third order fits to total power in the z -axis force signal for dithered cone textures in an unlogged plot. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.	241
A.23	Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the total power in the z -axis force signal.. . . .	241
A.24	Equations of 2nd and 3rd order fits to roughness versus element spacing in a log-log plot for five conical probe radii. The R^2 value for each fit is found beside it.	242
A.25	Coefficients of 2nd and 3rd order fits to z -axis velocity versus element spacing in a log-log plot for five conical probe radii. The R^2 value for each fit is found beside it.	242
A.26	Coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal versus texture spacing for five conical probe radii in a log-log plot. The R^2 value for each fit is found beside it.	243
A.27	Coefficients of 2nd and 3rd order fits to the roughness in a standard plot for the compliance experiment. The R^2 value for each fit is found beside it.	243
A.28	Coefficients of 2nd and 3rd order fits to the mean z -axis velocity versus element spacing in a log-log plot for four levels of compliance. The R^2 value for each fit is found beside it.	244
A.29	Coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal versus element spacing in a log-log plot for four levels of compliance. The R^2 value for each fit is found beside it.	244
A.30	Coefficients of 2nd and 3rd order fits to the roughness magnitude estimation data in a log-log plot for four levels of stick-slip friction (k_{Hay}). The R^2 value for each fit is found beside it.	245
A.31	Coefficients of equations for 2nd and 3rd order fits to the roughness magnitude estimation data in a log-log plot for two levels of viscous friction. The R^2 value for each fit is found beside it.	245
A.32	Coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal in a log-log plot. The R^2 value for each fit is found beside it.	245

A.33	Coefficients of 2nd and 3rd order fits to the z -axis velocity data in a log-log plot for four levels of Hayward friction K_{Hay} . The R^2 value for each fit is found beside it.	246
A.34	Viscous friction coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal data in a log-log plot. The R^2 value for each fit is found beside it.	246
A.35	Coefficients of 2nd and 3rd order fits to the mean z -axis velocity in a log-log plot for two levels of viscous friction. The R^2 value for each fit is found beside it.	246

Chapter 1

Perception of Virtual Textures

1.1 Introduction

1.1.1 Motivation

This thesis seeks to understand texture perception in virtual environments, apply its findings to a better understanding of the psychophysics of texture in general, and determine the fundamental physical properties which underly texture roughness perception. It proposes that virtual texture simulations must account for probe size, shape and compliance in order to produce virtual textures with perceptual characteristics that are similar to real ones.

The need for a study of virtual texture is driven by the increasing use of *haptic* devices to generate virtual environments for training and teleoperated tasks. These devices create the sensation of touching a virtual environment through the use of force-feedback and vibration. Contact with a virtual world is modeled and passed to the user's hand and fingertips via a mechanical interface. While much of the early work in haptic simulation focused on teleoperation and large-scale environments, recent improvements in device fidelity now offer the opportunity to render small scale environments like textured surfaces. High device stiffness, fine resolution and high position bandwidth make realistic haptic texture a possibility.

The ability to feel a realistic textured surface can be important for many tasks. Virtual texture simulations could improve teleoperated manipulation, lend fidelity to training simulations and make immersive artificial environments more realistic.

For example, we can imagine a teleoperation system which involves grinding a surface in a remote environment. Judging surface finish is a task for which vision is inadequate. Touch, however, can detect the presence of a single surface asperity of as little as 1-3 microns [57], a change in

sinusoidal texture amplitude of 1-5 microns [67] and 1-2 degrees of change in a curve's path [143]. If teleoperators are provided with a realistic sensation of texture roughness they should be able to judge the surface finish remotely.

Realistic texture can also be important in medical training and procedures. For example, the rash associated with scarlet fever is usually described as being "sandpapery" to the touch [15]. It is difficult to convey this to a medical student without the presence of an actual patient. A realistic simulation would permit students to learn about the disease prior to making a real-life diagnosis. Texture simulation could also be used to enhance surgical laparoscopic training and clinical procedures. Diseased tissues often have different textures than those of surrounding healthy structures. For example cirrhotic livers are often described as having a nodular surface[1]. The identification of tumor margins is very important for adequate excision [121] and may be aided by sensations of hardness and texture. Providing a realistic texture perception of laparoscopic surgical environments would add an important sensory modality to such techniques.

In the settings just described, the realism of texture perception is very important. It is generally accepted that a realistic experience in a haptic virtual environment contributes to task performance and helps to transfer real skills to the virtual world. Many studies, including our own, suggest that haptic feedback improves task performance [83, 122, 123, 137, 140, 144]. Low levels of friction, for example, can improve speed and accuracy in targeting tasks [112]. To allow the user to extract useful information from touching a virtual world it is important to appeal to their knowledge of real world sensations. Generally, the more closely the haptic interaction parallels reality, the more the user can rely upon real world intuition to perform tasks in the virtual environment. If a virtual environment is being used for training, it is also important to simulate qualities which are critical to task performance in a real environment. Artificial task constraints such as virtual fixtures [10, 11, 85, 89, 114] may make the task easier in simulation but could result in the development of skills which cannot be transferred to the real world. A realistic virtual environment means skills acquired during training should be useful in real settings. Thus physical stimuli yielding distinct perceptions in the real world should ideally produce the same kind of perception when simulated in a virtual environment. The violin should sound the same on a stereo as it does in concert. An important question to ask, therefore, is how real are virtual haptic textures?

The study of the relationship between a *stimulus* and humans' subjective sense of it, or *perception* of it, is called psychophysics. To build realistic simulations we need, first of all, to understand

the psychophysics of texture perception. What are the physical properties that produce the sensations of texture? How are they sensed by the skin, transmitted by the nervous system and processed by the brain? What are the important contributing factors for realistic virtual texture perception? Is it possible to develop a texture model that produces perceptions of virtual texture identical to those of real textures? Can modeled texture be used to provide deeper insight into the psychophysics of real texture? These question will be addressed by this thesis.

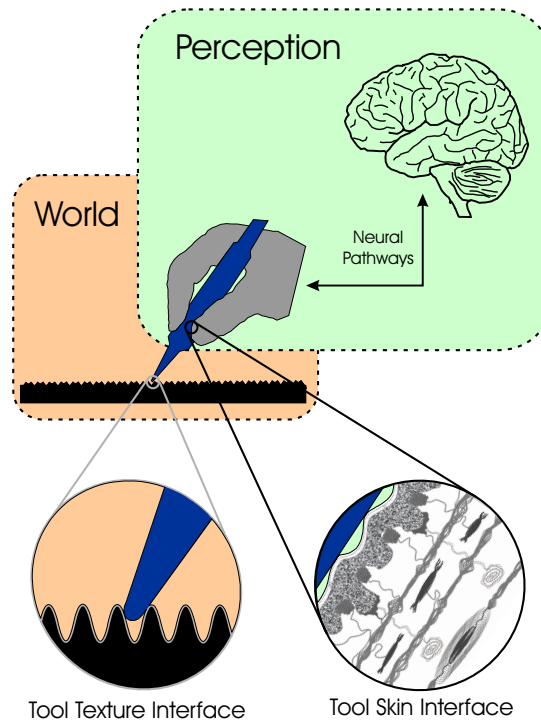


Figure 1.1: Transmission of texture information from physical world to the brain.

Texture perception is a complex phenomenon. Multiple ways of describing texture exist. For example, some studies have shown three or four roughly orthogonal perceptual axes exist for texture [50, 52, 54, 110, 135]. Hollins, for example, found hardness, stickiness, roughness, and vibration to all be important texture axes [52, 54]. Of these four, roughness has received considerable attention in the psychophysical literature [12, 18, 20, 23, 24, 62, 65, 68, 74, 81, 91, 93, 107, 108, 126, 132, 134, 141, 157]. The greater part of this work has been carried out on real-world textures, exploring the psychophysics of touching texture with a finger. Texture roughness perception is, however, significantly different when the texture is explored using a probe such as a pen or stylus rather than the bare hand [63, 65, 66, 74, 76, 79]. The type of probe used to feel the texture may have a direct impact on the user's perception of texture. We know, for example, that sweeping a spherically tipped

probe across a dithered set of conical elements can result in a perception of greater roughness if the probe is small rather than large [66].

It is possible to think of the probe as a link between the environment and human perception (see Fig. 1.1). It serves as a conductor of information which flows from the environment, through the probe-texture interface, and acts as an extension of the sensors in the fingertips. More than just a passive sensor, the interaction between the probe and texture generates a signal which is sensed at the probe-skin interface via the skin touch receptors. This signal is then carried along the neural pathways to the brain where it is processed and perceived. Clearly, the way in which the probe generates and modifies texture information will be an important component in our perception of the environment. Probe characteristics such as size, shape and compliance can be expected to change the nature of the information that eventually arrives at the central nervous system for evaluation.

The use of a virtual probe in psychophysics experiments allows control and isolation of variables which may be difficult to evaluate in the real world. Variables such as probe size, shape and compliance can be varied continuously and independently, reducing cost and setup time. This facilitates a detailed examination of the physical properties underlying the perception of texture roughness. Comparisons between real and virtual environment findings should provide important insights into the construction of better virtual environments.

Currently, users interact with virtual textures using a physical manipulandum which controls the location of a virtual probe in the simulated environment. The design of this probe has received little attention until now in the haptics literature, with most researchers focusing on developing algorithms to simulate the textured surface and not the probe. Probe characteristics are usually simplified to reduce computational complexity. A single, infinitely small interaction point is commonly used. Potential probe characteristics such as size, shape and compliance and their effects on user's environmental perceptions have been largely ignored.

One of the motivating factors for this research has been the detection of discrepancies between real and virtual environments with respect to texture perception [68, 91, 107]. It is possible that the haptic hardware is, itself, incapable of rendering some aspect of texture necessary for realistic perception. For example, if vibrational effects are important for roughness perception, the stiffness of the device and its position bandwidth may be inadequate to produce realistic textures. It is also possible that these differences reflect ways in which the simulation model fails to capture essential details of reality. Recent studies suggest that a possible cause of the discrepancies is that a real probe has some finite size [105] while the modeled probe in texture simulations is usually a point.

This thesis seeks to better understand the psychophysics of texture perception when the probe is modeled as something other than a point. Particular attention will be given to determining the ways in which probe characteristics, such as size, shape and compliance affect the perception of texture roughness. The perceptual axis of roughness is selected for examination since it is well studied for real textures and thus comparisons may readily be drawn between findings here and those in the psychophysics literature. Differences will be determined between psychophysical findings with point probes and probes of greater complexity. The motion and forces which the probe undergoes during texture interaction will be examined concurrently with subjective perceptual responses and used to determine the physical antecedents of roughness perception.

1.1.2 Problem Description

This thesis seeks to answer three questions. First, how do probe characteristics such as size, shape and compliance affect human texture perception? Second, what is the relative importance of these probe characteristics when modeling texture in a virtual haptic environment? Third, can virtual haptic simulations be used to determine the underlying physical properties of texture perception?

The first question comes out of psychophysics. It has been partially answered for probe size using experiments with real probes and texture. Probe shape and compliance have not yet been investigated in either real or virtual settings.

The second question relates to the eventual implementation of texture simulations. Should probe size, shape and compliance be considered essential when modeling textures in a virtual setting or not? How important are these factors with respect to each other? To what degree does each factor matter? For example, is there an optimal compliance for the probe which yields realistic texture or should it be as stiff as possible?

The third question is important since the physical properties characterizing texture perception are not well understood. It is assumed that probe vibrations excite receptors in the fingertips but the significance of individual vibrational characteristics has not been determined. A virtual texture simulation provides a way to carefully control individual texture parameters. At the same time, it makes it possible to measure physical properties such as the position of the manipulandum and the generated forces during psychophysical studies. By comparing subjective human responses with simultaneous physical measurements, made during manipulation of texture parameters, it is possible to better understand the relationship between physical stimulus and perception.

In summary, this thesis will use psychophysical methods to investigate how the probe characteristics of size, shape and compliance affect user perception in virtual haptic environments. These studies will provide insight into the psychophysics of real and virtual texture perception, supply models for improved virtual haptic texture, and relate the perception of texture directly to its physical properties.

1.2 Background and Previous Work

This thesis seeks to determine how the roughness of texture is perceived in a virtual environment, to determine the effects of simulating probe-texture interaction when the probe is modeled with size, shape and compliance, and to determine the physical properties that characterize texture roughness.

Thus this thesis will utilize perceptual techniques from the field of psychophysics to analyze subject responses to an algorithmically generated texture simulation developed using techniques from the field of haptics.

In what follows, a brief description of psychophysics and perception is followed by a discussion of the magnitude estimation and just noticeable difference methods of assessing stimulus perception. More specific discussion of the definition of texture and techniques for its synthesis then follows. A summary of previous texture perception studies, upon which this thesis builds, concludes the discussion.

1.2.1 Psychophysics

Psychophysics is defined as “the quantitative branch of the study of perception, examining the relations between observed stimuli and responses and the reasons for those relations” [2]. It is the study of the subjective human perception of quantifiable physical stimuli.

The relationship between the level of physical stimulus required to produce a detectable change in a perceived sensation was originally described by Weber (1795-1878) as

$$k = \frac{\Delta I}{I} \quad (1.1)$$

where I is the magnitude of the stimulus intensity, ΔI is the difference threshold required to produce a just noticeable difference (JND) in sensation and k is a constant known as *Weber's Fraction* [120].

Fechner (1801-1887) assumed that JNDs at different stimuli levels represented subjectively equal units of sensation and thus the ΔI that was responsible for a JND could be used to measure the subjective magnitude of sensation. The relationship between the magnitude of a perceived sensation, S , and the magnitude of a physical stimulus, I (for example the perceived brightness of a light and its luminosity), could then be described by a logarithmic function [120]:

$$S = k \log(I), \quad (1.2)$$

While Fechner's Law, as this equation is known, works well for many stimuli in their mid-range, it has been shown to be unreliable at extremes [120, 151].

Stevens, in 1957, had subjects estimate the magnitude of a sensation from a stimulus of known strength. His empirical findings led him to relate sensation to stimulus strength with a power law:

$$S = kI^b \quad (1.3)$$

The exponent, b , can be determined empirically from magnitude estimation studies [120]. Significant questions as to the law's fundamental nature exist since individual responses may differ substantially from the averaged data [38, 87] but it is still useful for characterizing perceptual responses.

Magnitude estimation is a useful technique for determining the form of the psychophysical function [31, 90, 160].

$$\Psi(I) = S. \quad (1.4)$$

Free magnitude estimation asks subjects to assign numeric values to perceived sensations. The resulting estimates are then plotted against the corresponding stimulus values. In a log-log plot, if $\Psi(I)$ is a straight line, then the slope of the line is the exponent in Stevens' power law.

The actual magnitude estimation process involves asking subjects to assign numeric values on a self-determined scale to assess perceptual intensity. The scale is not assigned by the experimenter, nor is a base standard provided for comparison. The only limitation to the scaling is that values less than or equal to zero are not allowed. This prevents zero values from invalidating geometric mean calculations, used to normalize magnitude estimates across subjects. Magnitude estimation with a

standard is an alternative technique for determining $\Psi(I)$ but the standard chosen may influence the shape of $\Psi(I)$ and has no significant advantage over free magnitude estimation [31].

There is, of course, no requirement that $\Psi(I)$ be linear in a log/log plot, although many different stimulus/sensation functions follow this pattern.

As previously stated, the threshold at which a change in stimulus can just be detected is referred to as the just noticeable difference. Various techniques exist for determining the JND.

Adjustment techniques require subjects to adjust the stimulus themselves until differences are noted. The adjustment technique relies on the subject's control and as such may be difficult to standardize.

The method of constant stimuli utilizes a set of stimuli with intensity values that bracket the approximately known threshold. Subjects are presented with each stimulus multiple times in random order and asked if the stimulus is present. The number of times the stimulus is detected is determined for each intensity level as a percentage of the number of times it is presented. These percentages are then plotted against stimulus intensity yielding the psychometric function (not to be confused with the psychophysical function, $\Psi(I)$). This function is commonly a sigmoid and the threshold is usually taken to be the stimulus intensity at which it crosses the 50 or 75% level of accuracy. The method of constant stimuli is the most reliable JND technique, however, it can require a significant commitment of time from subjects since multiple stimuli are presented repetitively in order to acquire significant statistical power [31].

The method of limits uses small fixed step sizes to increment a comparison stimulus, δ_{stim} , which is then compared to some fixed reference stimulus [31, 84, 120]. When a difference between the two stimuli is noted, the JND is considered to be the difference between the reference stimulus and δ_{stim} on the final step.

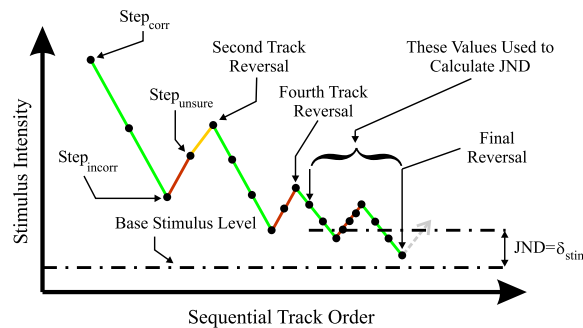


Figure 1.2: Determining JND using unforced weighted up-down adaptive threshold estimation.

Adaptive techniques are a variant of the method of limits. These techniques use a staircase method to rapidly bring the comparison stimulus down until it can't be distinguished from the reference stimulus. Subjects start with the comparison stimulus at a level where it is easily distinguishable from the reference stimulus. They are asked to identify the greater of the two stimuli. Correct responses result in a reduction of the comparison stimulus, stepping towards the reference stimulus. Eventually an incorrect response is made. At this point the staircase is reversed and the comparison stimulus is increased away from the reference. A series of oscillations about the threshold ensues and, after a pre-determined number of changes in track direction, the mean of the last few differences is taken and considered to be the JND (see Fig. 1.2). Step sizes can be decreased as the experiment progresses, improving the resolution of the threshold determination [31, 60, 84].

A threshold performed in this way is one at which subjects have a 50% correct rate. The percent correct performance level can be changed by altering the number of correct or incorrect answers given prior to taking a step down or up respectively. Thus the commonly used *two-down, one-up* staircase procedure has a 70.7% correct target threshold [84].

The technique used in this thesis to determine JND is Kaernbach's unforced weighted up-down (UWUD) adaptive staircase (see Fig. 1.2) [60]. This technique is a staircase which uses a variable step-size to target thresholds to any desired percent correctness level, P_{equ} . The step sizes $Step_{corr}$, $Step_{incorr}$, and $Step_{unsure}$ are defined to be the initial step-sizes for responses that are correct, incorrect or unsure. Given a desired P_{equ} , $Step_{incorr}$ and $Step_{corr}$ are related by

$$\frac{Step_{incorr}}{-Step_{corr}} = \frac{P_{equ}}{1 - P_{equ}} \quad (1.5)$$

and where N is the number of possible responses

$$\frac{Step_{unsure}}{-Step_{corr}} = \frac{P_{equ} - \frac{1}{N}}{1 - P_{equ}} \quad (1.6)$$

Both $Step_{incorr}$ and $Step_{unsure}$ are negative in sign and step the track away from the base stimulus but $Step_{unsure}$ is smaller than $Step_{incorr}$. All step sizes are reduced by half at 2 and 4 reversals of the track. Once eight reversals have occurred the JND is determined as the mean of all δ_{stim} 's from the value just after the fourth reversal to the value of the eighth reversal.

The technique is unforced since it allows subjects to express uncertainty. This reduces subject discomfort and has only minimal effect on thresholds [60, 84].

Two other techniques for JND determination include parameter estimation from sequential testing (PEST) and maximum likelihood techniques. These techniques are fairly complex to implement. Maximum likelihood techniques assume that the underlying psychometric function has a standard sigmoid shape [31, 84].

The adaptive staircase UWUD technique of Kaernbach is relatively straightforward to implement. When the stimulus is easily modified across a continuous range of values, such a technique can afford considerable time savings over the method of limits or the method of constant stimuli.

1.2.2 The Psychophysics of Texture Perception

This thesis will apply the psychophysical methods discussed above to the study of texture perception using virtual haptic textures.

Definition of Texture

There is currently no consensus in the psychophysics literature on what constitutes a formal definition of texture. Typically, texture has been investigated as small-scale surface phenomena which primarily activate skin sensors [12, 20, 23, 27, 28, 36, 71, 72, 78, 93, 119] rather than larger scale phenomena which may be primarily experienced via kinesthetic senses. Attempts have been made to define perceptual axes for texture using multidimensional scaling techniques [50, 52, 54, 110, 135, 156]. These studies have determined that three or at most four axes can be used to define texture. Unfortunately, the definition of these axes is not consistent in the literature. Roughness, stickiness, hardness and vibration are one such set [50, 52, 54]. For the purposes of this thesis, texture will be defined perceptually along the roughness axis. The roughness axis has been well studied and numerous comparisons may therefore be made between the findings found in the present work and the psychophysics literature [12, 18, 20, 23, 24, 62, 63, 68, 74, 81, 91, 93, 107, 108, 126, 132, 134, 141, 157].

The computer graphics community has also failed to reach agreement on a definition of texture [29, 113, 127, 128, 131]. Three broad descriptors of texture exist in this field: statistical descriptions of spatial distribution [155], spectral descriptions of the periodicity of texture features [17, 29], and structural descriptions of the geometry and composition of small elements which make up a texture [113].

The textures considered in this thesis may be described in terms of each of these definitions. For example, the constraint surface algorithm used here (see Section 2.2) to generate virtual surfaces, defines texture on the basis of the geometry of probe interaction with elements on a surface. These elements have some statistical distribution - either regular, in the case of sinusoidal gratings and trapezoidal texture - or stochastic, in the case of zero-mean white noise dithered cones. The motion of the probe over the elements results in periodic position and force signals which may be characterized by spectral analysis.

The concept of resolution is also important for texture definition in graphics [127, 128]. Objects seen at one scale may be perceived as texture but when seen at smaller scales may be perceived as distinct objects.

For haptic textures, resolution appears to be linked to the temporal frequency with which elements are encountered. For example, with high exploration speeds and/or closely-spaced elements, the individual elements are encountered frequently and subjects report feeling texture. At lower speeds and/or widely-spaced elements, individual elements are encountered less frequently and can be explored individually; in this case subjects fail to perceive the surface as textured.

The limiting temporal frequency at which subjects perceive a surface as textured and not as distinct elements could serve as a formal perceptual definition of haptic texture. Unfortunately, such a limiting frequency and its relationship to exploration speed and element spatial period remain to be determined.

In this thesis, subjects are not formally asked to say if a particular element period is *texture* or not. Rather, the range of element spacings and the size and shape of the elements is kept consistent with the psychophysical literature's implicit definition of texture. For the purposes of this thesis, then, texture will be arbitrarily defined as regularly or irregularly repeated geometric elements of less than 0.5 mm height, with periods or spacings of less than 10 mm which are not experienced perceptually as distinct elements given sufficient exploration speeds.

Texture Perception using Direct and Indirect Touch

Psychophysics explores how the various physical stimuli encountered in day-to-day life relate to the sensations that they produce. Psychophysical texture studies seek to explain how human perception is affected by the physical nature of texture, by the way in which the texture is manipulated,

and by the neural and cognitive processes associated with the perception of textural qualities. Understanding texture perception in the real world will lead to a better appreciation of the needs and requirements for virtual texture simulation.

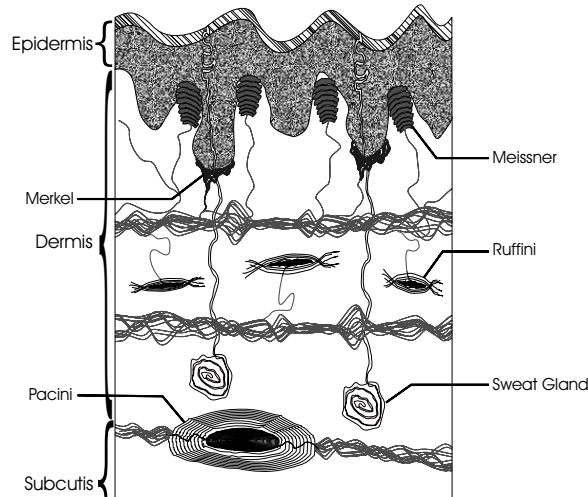


Figure 1.3: Skin touch receptors.(after Valbo and Johansson [142].)

Psychophysical studies of texture perception have a rich history, with the first documented study conducted by Katz in the 1920's in which he demonstrated that subjects could discriminate between grades of paper when writing on them with a pen [69].

In spite of such early work, an understanding of texture perception has been slow to develop. For example, the question of whether or not texture perception is mediated by vibratory/frequency stimuli or by energy/spatial stimuli long remained open [133]. In 1974, Lederman conducted experiments investigating the perceived roughness of finely grooved plates by human subjects when touched with the bare hand. This work demonstrated that roughness perception was little affected by hand speed. She also determined that increased hand force led to increased roughness perception and that roughness perception increased as groove width increased [81]. These findings led her to reason that roughness perception was related to the spatial effects of finger skin deformation and that temporal effects played little, if any, role in texture perception.

Further studies showed that depth of finger penetration into a groove, cross-sectional area of the finger in the groove, and cross-sectional area of the deviation of finger skin from rest, accurately predict roughness perception [132]. These studies clearly seemed to indicate that roughness perception was mediated by spatial, not temporal, stimuli.

Afferent Type	FA1	FA2	SA1	SA2
Receptor	Meissner	Pacinian	Merkel	Ruffini
Frequency range*	5-50 Hz	50-700 Hz	<5Hz	?
Indentation Amplitude Threshold	6 μm	0.08 μm	30 μm	300 μm
Receptive Area	22 mm ²	Entire hand	9 mm ²	60 mm ²
Spatial Acuity	3 mm	10+ mm	0.5 mm	7+ mm

Table 1.1: Mechanoreceptor afferent systems and their properties. Adapted from Stevens' Handbook of Experimental Psychology, Chapter 13: The Neural Basis of Haptic Perception [59]. *Frequency range is from Sensation and Perception, 2nd edition [154]

Studies of the neurophysiologic response to texture confirmed this. There are four kinds of touch receptors in the skin of the hand [14, 25, 142] (see Fig. 1.3). Each responds to a different stimulus and has its own threshold and resolution (see Table 1.1). Fast adapting units (FA1 and FA2 - Meissner and Pacini units respectively) respond to sudden changes and have little static response while slowly adapting units (SA1 and SA2 - Merkel and Ruffini units respectively) respond to slow and static changes in the skin [59, 142]. The FA units are thought to respond to temporal/frequency cues while the SA units are likely responsible for spatial ones.

The precise nature of the relationship of the four touch receptor units to the perception of texture has seen considerable investigation with neurophysiologic studies. These studies directly examine the firing rates of the primate nerves associated with the receptors in question while a textured surface is passed over the skin. The firing rate patterns are then compared to perceptual responses by human subjects using the same textures. This technique assumes that if a particular receptor's neural response correlates with perceptual responses, then that receptor is responsible for the perception under study [23, 73]. Early studies by Darian-Smith *et al.* demonstrated that SA receptors encoded coarse dots well while FA1's and FA2's had possible temporal coding [27, 28] although Lamb found that direct perception of roughness increased with element spacing as did FA mean firing rates but SA's did not [71, 72]. An extensive series of studies by Johnson's group determined that spatial coding by the SA's was the most likely neural mechanism for direct roughness perception although FA's were thought to possibly provide a sense of slip, flutter and motion [12, 20, 23].

As the properties of the cutaneous touch receptors in the human hand became better known, studies were designed to selectively adapt the FA receptors to vibrational frequencies known to

stimulate them. By prolonged stimulation of the fingerpad with frequencies to which the FA receptors normally respond, they can be made to effectively turn off, a process referred to as *adaptation*. This results in a loss of vibration sense. Subjects were asked both before and after adaptation to assign roughness perception magnitudes to stimuli composed of gratings with varying spacings. It was found that there was little change in subjects' ability to perceive roughness even when they could not perceive vibration. This supports the view that texture perception with the bare hand is unrelated to vibration [78].

Recent studies indicate that, while spatial effects predominate with direct texture perception, vibrational and temporal cues may provide an alternative channel of information [18, 35]. It has been shown that, while selective adaptation of vibrational receptors (FA1's and FA2's) does not eliminate roughness perception itself, changes in the quality of roughness do occur [36, 51]. Cooling of the ulnar nerve makes surfaces feel smoother [25], a phenomenon thought to relate to an inhibition of high frequency discharge patterns. Hollins *et al.* developed a duplex theory of texture perception [49, 51, 53]. They showed that directly experienced roughness of textures with periods less than 0.1-1 mm may be mediated via vibratory frequency cues while textures with periods larger than this may be mediated by spatial cues. Thus, while direct roughness perception is largely mediated by spatial effects, it seems clear that some part of the experience is mediated by vibration.

The interposition of a rigid link, such as a probe, between surface texture and the user removes the possibility that spatial effects (such as those seen when the finger skin is deformed between grooves) can mediate roughness perception. It would seem impossible, therefore, that a probe could be used to feel texture. This, however, is not the case. In fact, some studies demonstrate that for surfaces with finer textures, the probe provides better roughness perception than the bare finger and in most other cases is only slightly worse [65, 74, 77]. It is also found that as a textured surface's groove spacing increases, so do roughness estimates of the surface, reaching a maximum after which the estimates decrease again [65]. These findings suggest that in the absence of spatial information, vibratory information *can* be used to determine roughness accurately. This is confirmed by the fact that roughness estimates using a probe *are* affected by changes in probe speed [65] in contrast to Lederman's work with the bare finger. A roughly quadratic shape of roughness perception versus groove spacing was also noted in this study and reasoned to be due to the relationship between probe size and groove width.

Interestingly, texture perception studies using a point-interface virtual probe on sinusoidal gratings demonstrate that as groove width (and thus period) increases, roughness perception usually

decreases steadily [68, 91, 107, 147]. The quadratic roughness perception function is not seen. Penn *et al.* speculate that this is due to the infinitesimal nature of the haptic interaction point used in their virtual haptic model [107]. The haptic interaction point follows the sinusoid exactly, regardless of period and thus shorter periods result in higher frequency vibrations and increased changes in force along the direction of the probe axis. The rate of change of tangential force on the finger pad during direct touch has also been shown to be correlated with human roughness estimations: the higher the rate of change, the higher the roughness estimate [126].

Minsky and Lederman have demonstrated that for a 2 DOF haptic device which simulated only lateral forces, roughness perception correlated closely with force amplitudes [95]. The idea that lateral forces may be the most important element of texture perception has received some support from Ho *et al.* who found that subjects couldn't tell 2D from 3D gratings when periods and amplitude were small [47]. However, they used very low texture stiffnesses (2 N/mm) so that subjects could easily pass through gratings with their point-interface probe. This results in lost positional cues that might be present if the probe were forced to ride across the texture. This thesis will use considerably higher stiffnesses for most experiments and will explore the effects of low compliance on perception.

Recently interest in how probe characteristics affect texture perception has developed. A study by Klatzky *et al.* [66] develops a geometric model of a spherical probe tip passing over a set of cylindrical or truncated cone shaped elements. The model seeks to predict the effect of changing probe size on roughness perception. In the case of a probe with real physical size, when grating periods are small with respect to the probe tip, the probe will travel along the tops of the grating elements, penetrating only slightly, if at all (see Fig. 1.4), bottom). Thus forces transmitted by the probe will tend to vary only slightly. As the period of the gratings increases, the probe tip will begin to penetrate more deeply between the gratings and, for a given probe speed, the force variations will increase. Once the probe is penetrating to the maximum depth and following the sinusoidal surface exactly (Fig. 1.4, top panel), roughness perception should be maximal (referred to by Klatzky as the *drop-point*). Further increases in grating period beyond this point result in decreasing force variation and thus result in lower roughness judgments.

The predictions for the real probe case have been experimentally verified by Klatzky *et al.* using spherical probes of varying tip size and jittered cylindrical and truncated cone elements. A geometric model of the interaction between probe tip and surface was used to predict the location

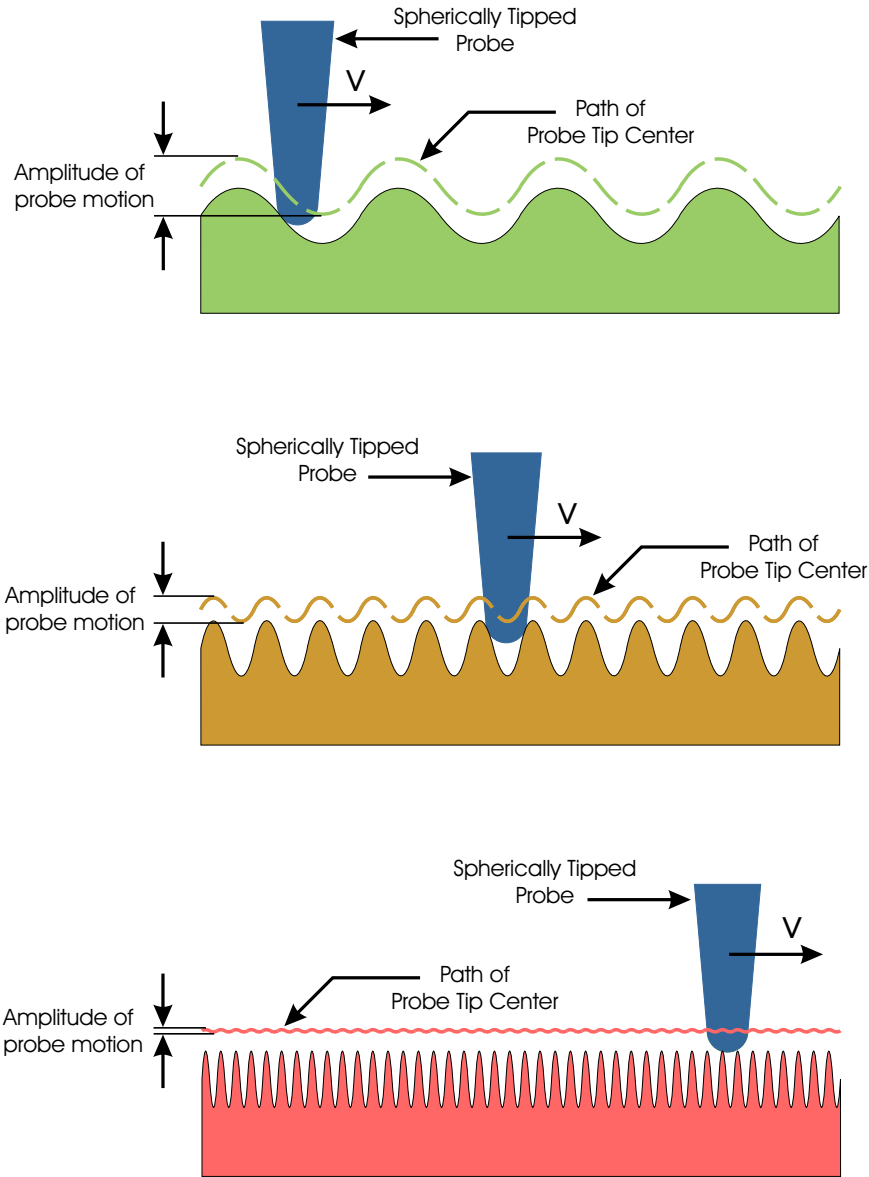


Figure 1.4: The effect of decreasing texture frequency on probe motion amplitude.

of the drop-point. It can be seen in Figure 1.5. The penetration depth d for the square grating is related to the radius of the spherical tip r and the inter-element spacing s by the formula

$$d = r - \sqrt{r^2 - (s/2)^2}, \quad (1.7)$$

while for trapezoidal gratings the depth of penetration is found from

$$d = (s/2) \tan \alpha - r(\sin \alpha \tan \alpha + \cos \alpha - 1). \quad (1.8)$$

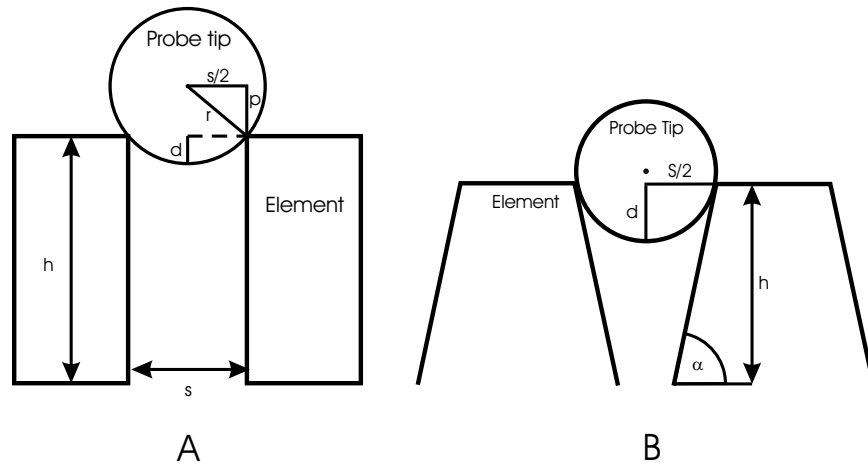


Figure 1.5: Two dimensional spherical probe tip with a.) square grating and b.) trapezoidal grating. (after “Perceiving roughness via a rigid probe: Effects of probe and surface geometry and exploratory factors,” Klatzky *et al.*) [66].

The model does not take into account probe/surface dynamics and is simply based on the geometric relationship of the spherical probe tip and element geometry. Correspondence between the model and findings was good, although a significant and consistent under-estimation of the measured drop-point by the model was noticed [66].



Figure 1.6: A PHANTOM™ Premium 1.0 device. (Image from Sensable Technologies)

There is some debate as to the shape of the psychophysical function for element spacing. Kornbrott *et al.* in 2007 [68], examined individual psychophysical functions for subjects exploring

a sinusoidal grating with a point-probe and determined that different subject populations existed. These populations all had linear functions with one population demonstrating an increasing $\Psi(I)$ and the other a decreasing $\Psi(I)$. The suggestion was made that by averaging these populations, an inverted “U”-shaped curve can be found for the population as a whole but this averaged curve does not actually reflect the perceptions of any individual. They argue that $\Psi(I)$ is inherently linear when examined on an individual scale. While it is important to examine individual responses as well as aggregated ones, it is also possible that the differences noted between Kornbrott and Klatzky arise from a difference of approach. Kornbrott uses virtual sinusoidal grating textures with a point probe on a PHANTOMTM haptic device (see Figure 1.6). The PHANTOMTM is a mechanically driven device which suffers from frictional effects and backlash and has limited position bandwidth and stiffness [19]. Thus deficiencies in the haptic rendering hardware, as well as defects in the applied texture model, need to be considered as possible causes for differences in Klatzky’s and Kornbrott’s findings. Clearly a point probe is not identical with Klatzky’s spherically-tipped probes and a PHANTOMTM device is incapable of rendering real world stiffnesses. This thesis will demonstrate that the psychophysical function, as determined using real textures, can be found by applying a texture model that simulates real probe geometry.

The increasing use of haptic devices has led to interest in understanding how psychophysical findings from reality transfer to the virtual environment and *vice versa*. In the study by Penn *et al.*, mentioned above, the manipulandum used (stylus or thimble) was found to significantly change roughness perception [107]. The different manipulandi may have different amounts of compliance or differing resonant frequencies thus passing different information to the user about the virtual environment. Studies by Weisenberger and Krier demonstrate that both frequency and amplitude cues play a role in allowing subjects to distinguish textured features [153].

Penn’s group found that the amount of force applied to a virtual texture increased its perceived roughness even though the psychophysical function showed decreasing roughness perception with increasing groove width for all conditions [108]. The group also demonstrated that, if users were allowed to select force levels, they used the same force for all textures. This implies that subjects use their knowledge of the force they are applying as a factor in determining roughness. The force applied by a user may not be what they expect if probe compliance is unknown to them. Studies of how probe compliance alters roughness perception could thus potentially reveal details of non-force factors used in roughness judgments. Wall and Harwin found that subjects were better able to judge grating orientation when using a higher frequency haptic device [148]. This suggests that probe

characteristics such as damping may significantly effect roughness perception. Walker and Tan investigated how stiffness affects the perception of surface topography and found that the relative stiffness of two surfaces may affect users' ability to feel a step deformity [145]. All of these studies imply that compliance, whether of the probe, surface or manipulandum, is a significant factor in roughness perception.

Weisenberger *et al.* compared 2 DOF and 3 DOF devices [152]. Subjects were asked to detect the orientation of sinusoidal and square wave gratings. They found that the 3 DOF device showed significant differences between square and sine wave gratings while the 2 DOF device did not. They speculate that the speed of motion may have resulted in "incomplete sensing of the grooves of the square gratings." While the probe was a point in both cases, the addition of an extra dimension of motion allowed better perception of the gratings. Meyer-Spradow developed a mathematical model of probe shape for haptic rendering which incorporated probe shape as a component and demonstrated that roughness perception by human subjects changed with spherical probe size [94]. It seems that the interaction between the shape of the texture and the shape of the probe has an effect on roughness perception.

The actual physical properties underlying the perception of texture roughness have long been the subject of discussion. With direct touch, roughness can be related to the geometry of the surface, increasing with groove width [75], or with particle size, in the case of sandpaper [53]. It has also been found to increase with the coefficient of friction [32]. For direct touch, when dots are used as a textured surface, some authors have found simple linear relationships between regular dot spacing and roughness [93] and others have found results similar to indirect touch where the psychophysical function is an "inverted U-shape" [20, 66]. Both of these examples used a wide range of spacings from 0.8-1.5 mm as a minimum and 6.5-8.5 mm as a maximum. A major difference between the two findings was that the linear relationship was found with dot heights of 1.8 mm while the inverted U was found with heights of 0.35 mm.

Indirect touch has only recently been examined, although correlation between lateral force amplitudes and tangential changes in force have both been implicated in roughness perception [95, 126]. Geometry clearly plays a role in roughness perception as a texture of dithered conical elements results in a roughly quadratic-shaped psychophysical function [66, 141] while sinusoidal gratings produce variable results [68, 91, 107, 147]. It is likely that the mechanoreceptors of the skin are responding to changes in position, energy or force that are induced by probe/texture geometric interactions. Lin *et al.* developed a texture algorithm that demonstrated, in simulation,

that a spherical probe on a sinusoidal texture will produce accelerations correlating with Klatzky's psychophysical functions for changes in probe size, applied force and probe velocity. [104, 105]. More recently, Yoshioka *et al.* examined roughness, hardness and stickiness with both direct and indirect touch in a real environment [156]. He determined that vibratory power correlated well with perceived roughness. Previous studies had implicated the Pacinian mechanoreceptors in the sensation of fine texture and correlated vibratory power, filtered by a function describing the Pacinian's frequency sensitivity, with roughness in direct touch [5, 6]. Yoshioka found that raw vibratory power correlated slightly better than filtered for indirect touch, although the results were almost indistinguishable.

In most of the preceding virtual texture studies, the probe was an infinitely small point, without shape, size or compliance. Yet each of these studies suggests that modeling such factors might lead to answers about the nature of texture perception. The following section discusses previous techniques for modeling textures and probes.

1.2.3 Texture Rendering

Probe Modeling

The development of a probe model in which the probe has variable size, shape and compliance is an important component of this thesis but probe modeling for texture exploration is not well discussed in the haptics literature.

A large number of algorithms exist for modeling contacts between rigid objects, as well as for generating textured surfaces (see below), but the probe is usually assumed to be an infinitesimal, infinitely stiff point. This reduces computational complexity but ignores the probe's role in the perceptual pathway. Device characteristics may also prevent certain aspects of the probe from being simulated. Poor position bandwidth characteristics may limit the power spectrum, which, if texture roughness perception relies on vibrational power, may prevent a realistic texture experience. Poor resolution may limit the kinds of texture geometry that may be displayed. Devices that have poor levels of maximum stiffness may be unable to display the tangential force variabilities associated with texture.

Some of the shortcomings of point-based haptic interactions include the possibility of punching through thin objects and force discontinuities encountered when points pass over object vertices. Techniques to overcome these shortcomings involve placing a virtual proxy, called by its originators

a “God object”, around the haptic interaction point [115, 118, 159]. The virtual proxy can be any shape but is often spherical. Interaction forces between the object and the surface are calculated and forces applied to the haptic interaction point (HIP). Thus, for example, the sphere cannot penetrate into small crevices or pass entirely through a thin object. As it passes around sharp corners, the path of the haptic interaction point is smoothed. An extension of this technique developed for use in this thesis and referred to hereafter as the constraint surface algorithm (CSA), is used to generate textures where the probe has some shape or size.

Efforts have been made to use more than one device to model probes with shape. For example, Ho, Basdogan and Srinivasan proposed a ray-based probe model for interaction with 3D objects [45]. This system incorporated two PHANTOMTM devices to simulate a ray-shaped probe through which the user could experience forces and torques. The probe was capable of multiple point-face, ray-edge, and ray-face type contacts with polygonal models along its length. Tests showed that using a ray-based probe significantly improved object recognition. Wall has proposed a design for a system which uses three PHANTOMTMs to simulate grasping an object [149]. In this case the probe would be three points, as opposed to just one.

Devices with 6 DOF are becoming more common and simulations in which the probe is a 3D object, moving freely in space and having material characteristics such as weight, are becoming possible. For example, Berkelman, in 1999 demonstrated a 6 DOF system in which the probe could be an arbitrarily shaped polygonal object [9]. In his system the interaction between probe and objects was calculated by a dynamics engine and the haptics probe was coupled to the dynamics engine probe by a virtual spring. The probe thus had size, shape, and compliance. Unfortunately the dynamics engine was unable to run at the same rate as the haptic servo loop resulting in lag and sticking behavior especially during complicated interactions. The high level of complexity of textured surface simulations seems to preclude the use of such polygon-based probe-surface models due to computational intensity.

Recent work by Otaduy and Lin has led to the development of a force model capable of rendering interactions between two textured objects [104, 105]. Their algorithm calculates forces and torques based on the gradient of penetration depth at a local level, between textured surfaces. They use the gradient of object interpenetration because of “the influence of probe geometry” on roughness perception. Their model is capable of update rates on the order of 100-200 Hz when there are 5-10 contact patches between objects. Using a model of human dynamics as an input to their model, they were able to demonstrate, in simulation, that maximum acceleration of the probe followed a

quadratic function over element spacings. The function varied with probe diameter, applied force and exploratory speed in ways which were similar to previous psychophysical studies of the same factors [79].

Several high speed algorithms for haptic rendering of polygonal objects exist [41, 58]. They concentrate on rigid body collisions and interaction between objects with several hundred to thousands of polygons but have not been used for texture simulation.

A volumetric approach to rendering has also been proposed [92, 150]. In this model, the most computationally expensive part of rendering interactions between objects, collision detection, is simplified by discretizing all objects and free-space into voxels. Collision detection then occurs if voxels from two objects occupy the same coordinates. This technique requires considerable memory but is able to render moderately complex probe shapes in interaction with large static environments at high rates.

Techniques exist for rendering haptic compliance. The simplest of these is the penetration depth penalty method [118]. This assumes that the surface-probe interaction has some element of compliance which is the same for all objects. As the haptic interaction point penetrates the surface, the depth of penetration is used to calculate a restoring force, opposite to the direction of penetration. Usually, the surface is assumed to be compliant while the probe is thought of as infinitely stiff.

Simulations of finger pad friction and compliance characteristics are perhaps the most developed example of modeling probe compliance properties [100]. In these experiments, the force-displacement relationship between tangential forces and finger pulp displacement are found and used to simulate the *feel* of a finger pad sliding over an object. The haptic probe thus has some of the characteristics of the human finger, although it remains a point contact.

Finite element models (FEM's) have also been used in haptic virtual environments to describe encountered objects [56, 158]. The stiffness matrix of a 3D FEM defines the object's compliance while the layout of the mesh defines the object's physical shape and size. FEM's would thus be ideal for simulating the size, shape and compliance of a probe. Unfortunately, their computational overhead has made them unsuitable for real-time haptic simulations and their use as probes in texture simulations has been unexplored.

It can be seen from the preceding brief survey that, while techniques exist for modeling probe size, shape and compliance, the probe has received little attention from the haptics community. In some cases, such as the virtual proxy, ray-based probe and finger pad models, it is recognized that it

is important to model probe characteristics in order to provide more realistic or detailed interaction with a simulated environment. This thesis will use some of these known techniques to simulate the probe's size, shape and compliance. The algorithm chosen for texture simulation is a modification of the virtual proxy technique and operates strictly along the z axis. Thus, desired positions and forces are all applied along one translational axis while rotation is prevented. Users are free to move the probe along the x and y axes. This version of a virtual proxy works well for texture, which is planar in nature and still allows manipulation of probe size, shape and compliance while reducing the complexity of the psychophysical analysis to a single axis.

Texture Modeling

The preceding section discussed various techniques for modeling the probe which will interact with a textured surface. A key point of this thesis is that it is not just the probe, or just the texture, that produces texture. Rather, it is the interaction between them which governs perceived roughness. A suitable texture algorithm for this thesis would be one in which the geometry of the texture was repeatable, variable in real time, and permitted the calculation of a constraint surface without excess computational overhead. There exist many different techniques for modeling texture, the bulk of which can be divided into two types: image-based and procedural texture models [3]. A brief discussion of the background of each type follows as well as a discussion of their suitability for use with a constraint surface.

Image-Based Modeling

Image-based modeling techniques rely on mapping a pre-computed force or displacement image to the position of the haptic device endpoint. Using this technique it is possible to render 2D images, such as X-rays or photos, haptically. Texture perception studies with Minsky's *Sandpaper* system used height maps of grids, Perlin textures (terrain created from band-limited noise [109]) and $1/f$ noise images, to calculate tangential forces felt as the subject moved over a surface [96]. Costa developed fractal images to simulate rock surfaces using quantifiable measures from surface metrology [24]. These surfaces were then displayed using a 3 DOF PHANTOMTM haptic device. This image-based technique has also been used to map 2D texture images to virtual 3D objects [46]. The image-based techniques provide repeatability, anisotropy and low computational overhead during rendering, since the force or height for any set of surface coordinates is simply a table lookup.

However, it may require substantial precomputation and significant memory resources if the texture maps are rendered with a high level of detail.

Procedural Modeling

Procedural models calculate force or surface height “on the fly” and may be divided into two subtypes: stochastic and deterministic.

Stochastic models use random noise to simulate forces arising from interactions between the asperities of common surfaces [34, 39, 124, 125]. These asperities are usually distributed in a random fashion.

Deterministic models define forces or surface heights as a function of the (x, y) position of the haptic interaction point. These models are usually simple since they must ideally be updated with each control loop of the haptic device servo. Hayward and Yi describe surface patches using

$$z(x, y) = \tan(\alpha)x + A\sin(wx)y, \quad (1.9)$$

where α is the underlying slope of the patch and finer surface detail is controlled by the amplitude, A , and period, w , of a sine wave. They then generate lateral forces from the height gradient along the line of motion [44]. Minsky’s system also does this but uses an image based height map rather than a procedural one. Force mapping, another technique similar to the bump mapping texture techniques used in graphical rendering [13], perturbs the normal vector of a surface according to some function based on the haptic interaction point surface coordinates [21, 115, 118]. Usually, forces applied to the user are based on a height map which may be generated beforehand or calculated as a function of surface position. Ho *et al.* report generating procedural textures using Perlin noise, reaction-diffusion textures, spot noise and cellular texture [46].

Force perturbation techniques have also been used to generate stochastic textures [34, 124]. In this technique the surface normal may be perturbed by a noise function. Since the perturbation of the surface normal is sensed as forces at the hand, it saves computation time to perturb the world space forces rather than alter the surface norm from which they are calculated. By modifying the mean and standard deviation of Gaussian noise it is possible to generate distinguishable textures. It is possible to generate more complex textures by spectral shaping of the white noise power spectrum using filters [34]. It is also possible to model surface characteristics based on measured frequency characteristics of either surface displacement [146] or force variation [86].

This thesis is interested in rendering repeatable realistic textures in order to perform reproducible psychophysical experiments. The constraint surface algorithm uses a base image in which the location of elements is pre-mapped. It also implements procedural techniques to determine the desired location of the HIP, using the pre-computed locations of elements to determine parametric equations that define the texture. This combination of image-based and procedural texture makes it possible to have the advantages of image look up (fast computation of collision and repeatability) and the flexibility of procedural textures based on parametric equations.

1.3 Approach

This thesis poses three questions, of which the first is the most fundamental: How do probe size, shape and compliance affect texture perception? This question will be approached by first developing a set of algorithms which provide a simulation of these factors and their interaction with texture. Human subjects will then explore the simulated textures using a haptic device and estimate the roughness magnitude of the encountered texture. By examining this perceived roughness over a range of texture element spacings, a psychophysical function, $S = \Psi(I)$ can be found. The function relates texture stimulus intensity, I , which for this thesis will always be element spacing or period, to perceived sensation, S , which is the subject magnitude estimate of surface roughness. For most such experiments, several $\Psi(I)$ functions, corresponding to different levels of the primary experiment factor (for example probe radius) will be defined. For example, during probe size experiments, probes with four different radii are used and four $\Psi(I)$ functions are found which relate subject magnitude estimates to texture spatial period. The shape of the psychophysical functions is determined using polynomial fitting and comparisons are made between functions within each individual experiment as well as across experiments. Similarities and differences between the functions will reflect the relative importance of modeling probe characteristics thus answering the second question in our problem description.

The third question seeks to identify the underlying physical properties that are felt as texture when indirect touch is used. Real-time high frequency (1000 Hz) recordings are made of the position and orientation of the haptic device manipulandum during each experimental trial along with the forces and torques output by the device to the subject's hand. These recordings are analyzed and compared, on a trial by trial basis, to subject responses about the perceived roughness where

each trial consists of a single subject roughness magnitude estimate based on a single probe-texture pairing.

These recordings allow examination of a multitude of physical properties including position and orientation in multiple axes, the first and second derivatives of position, kinetic energy, force and torque. For each of these properties, a variety of statistical and spectral analyses are possible. For each physical property measured, a physical function, analogous to the psychophysical function, will be created. This function, $\Phi(I)$ will relate the physical measure P , to the same stimulus intensity variable used in $S = \Psi(I)$, namely element period or spacing, thus $P = \Phi(I)$.

The two functions, $\Phi(I)$ and $\Psi(I)$ will be tested for correlation. A strong correlation will be considered evidence of causality; namely that the physical factor in question is perceived as roughness. Principle component analysis and multilinear regression will be used to further rank physical factors based on their influence.

Statistical analyses include mean, maximum and standard deviation measures. These measures are based on assumptions of how physical properties are sensed by the skin's mechanoreceptors. Mean measures assume that the sensors average the incoming signal, while maximum measures assume some threshold exists for triggering a sensor. The standard deviation measure assumes that it is the variability in the signal that produces a sensor response.

Spectral analyses include measures of mean signal power, frequency of maximum signal power and maximum signal power measures. Mean signal power is effectively a measure of signal variance and is based on the same assumptions used for the measure of standard deviation. The possibility that peak signal frequency, rather than average power is a sensor trigger is explored by examining the location of the peak frequency and the possibility that the maximum rather than the mean signal power triggers sensors is examined by the maximum signal power measure. It is also possible to apply these measures to band-limited portions of the spectrum. The vibrational frequency band limits for the four mechanoreceptors in the skin of the hand are fairly well known (see Table 1.1). The possibility that one kind of receptor may be responsible for roughness perception leads to an analysis of band-limited signal power based on known receptor frequency response characteristics.

The first three experiments in this thesis (Chapters 3, 4, and 5) deal with probe size. The first of these is a baseline experiment with sinusoidal grating textures and a point probe. This allows comparison with the literature. The second experiment deals with trapezoidal gratings, providing a texture which is a grating but whose elements are similar in shape to those in the third experiment which uses dithered truncated cones as elements. The second and third experiments may be

compared to determine the differences between regularly spaced gratings and randomly placed elements. The fourth experiment examines a change in probe shape which should have implications for subjective roughness assuming the geometric model holds (see Section 1.2.2). The fifth experiment examines the changes in perception that occur when probe compliance is modified. This experiment, and the last one on friction, examine the effects of “muddying the waters” perceptually. That is, how does perception of roughness degrade when signal strength decreases or noise is introduced.

A series of just noticeable difference experiments will also be presented. These experiments will examine the discrimination thresholds for roughness for varying levels of the probe factors: size, shape and compliance. JND’s have previously been determined for virtual texture amplitude using sinusoidal and saw-tooth gratings [67]. These virtual studies used point probes. This thesis is interested in how factors such as probe size, shape and compliance will alter discrimination thresholds. Defining the relationship of thresholds to these factors will be a significant archival contribution to the field of psychophysics.

Experiments will be performed using a constraint surface algorithm running on a magnetic levitation haptic device. Algorithm design and device characteristics will be the subject of the next chapter.

1.4 Contributions

The primary contributions of this thesis include the following:

- Demonstrating that the perception of virtual texture depends on modeling the geometry of both texture *and* the exploring probe’s size and shape
- Demonstrating how texture perception is altered by compliance and friction.
- Determining that texture roughness can be characterized by the physical property of force variability.
- Analyzing the force signal power spectrum to show that FA1 neural receptors are likely the receptors primarily responsible for mediating roughness perception.
- Creating a record of JNDs for virtual texture element spacing and its relationship to probe size, shape and compliance.

- Demonstrating that virtual haptic textures are a useful tool for performing psychophysical studies of texture perception and that virtual findings correlate well with real-world psychophysical properties.

Chapter 2

Experimental Setup and Design

Virtual haptic texture experiments require a texture model which can be implemented on a haptic device. In what follows, a magnetic levitation haptic device (MLHD) is discussed, along with its operating characteristics, bandwidth, workspace and controllers. The device will be used in conjunction with a constraint surface algorithm, to be described below (see Sec. 2.2), which produces a model of the probe/texture interaction. This algorithm will vary depending on size and shape of the probe as well as on the underlying texture geometry. Specific variants will be discussed later in the document. The experimental setup for measuring the psychophysical function for roughness will be described, followed by a description of the measurement of physical properties. Finally, the experimental setup for JND measurements will be discussed in detail.

2.1 Magnetic Levitation Haptics

In order to perform psychophysical studies of virtual texture a haptic device must be used which is capable of rendering textures with sufficient fidelity.

Typical haptic devices suffer from friction, backlash and inertia associated with their actuators and linkages. Their position bandwidths and resolutions are often insufficient to render the rapid vibratory motions associated with texture.

The magnetic levitation haptic device, designed and built by Peter Berkelman and Ralph Hollis at the Microdynamics Systems Laboratory at Carnegie Mellon University's Robotics Institute is a state-of-the-art, magnetically levitated, 6 degree of freedom (6 DOF) haptic device (Fig. 2.1)[8, 9]. The device design was based on a 6 DOF Lorentz magnetic levitation system, called the IBM Magic Wrist [55, 116, 117, 129].

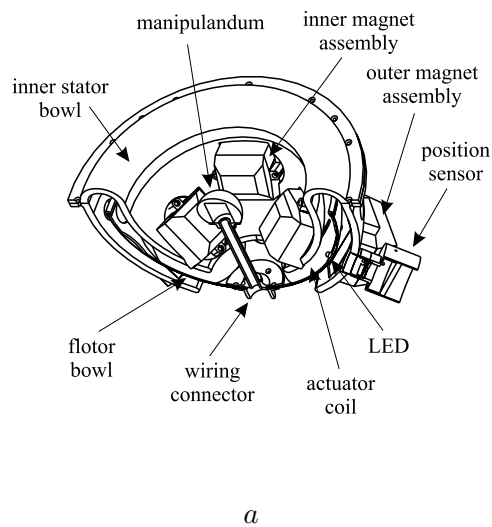


Figure 2.1: a.) Lorentz magnetic levitation device cut-away view of design. b.) Magnetic levitation device used as haptic interface to a virtual world

The device consists of a single hemispherical moving part, the flotor, which is levitated between a set of fixed magnetic assemblies, the stator. When current passes through any of the 6 coils set in the flotor's surface, Lorentz forces, from the interaction between the magnet assembly and the coil's current, generate a force on the flotor. With careful placement of the 6 coils and control of the currents, it is possible to generate an arbitrary force-torque wrench on the flotor. This wrench is transferred to the user's hand by a manipulandum, attached to the center of the flotor bowl. The flotor has 3 LED's on its outer surface which are sensed by photodiodes on the stator. Because the flotor is free floating and very light the device has low inertia and a high position bandwidth (125 Hz at ± 3 dB)[8]. It has a position accuracy of 5-10 μm and a maximum stiffness of 25 N/mm in translation and 50.0 Nm/rad in rotation. Its most significant limitation is its small workspace (± 12 mm in translation, $\pm 7^\circ$ rotation about any axis) [8]. A proportional-derivative (PD) controller running on an AMD 2100+ processor controls the device with a servo update rate of 1000 Hertz. A graphical workstation running on a separate processor provides visual feedback based on the device position which is communicated over a dedicated Ethernet link.

The MLHD's high position resolution, position bandwidth and stiffness make it an excellent platform for simulating texture and probes with size, shape and compliance.

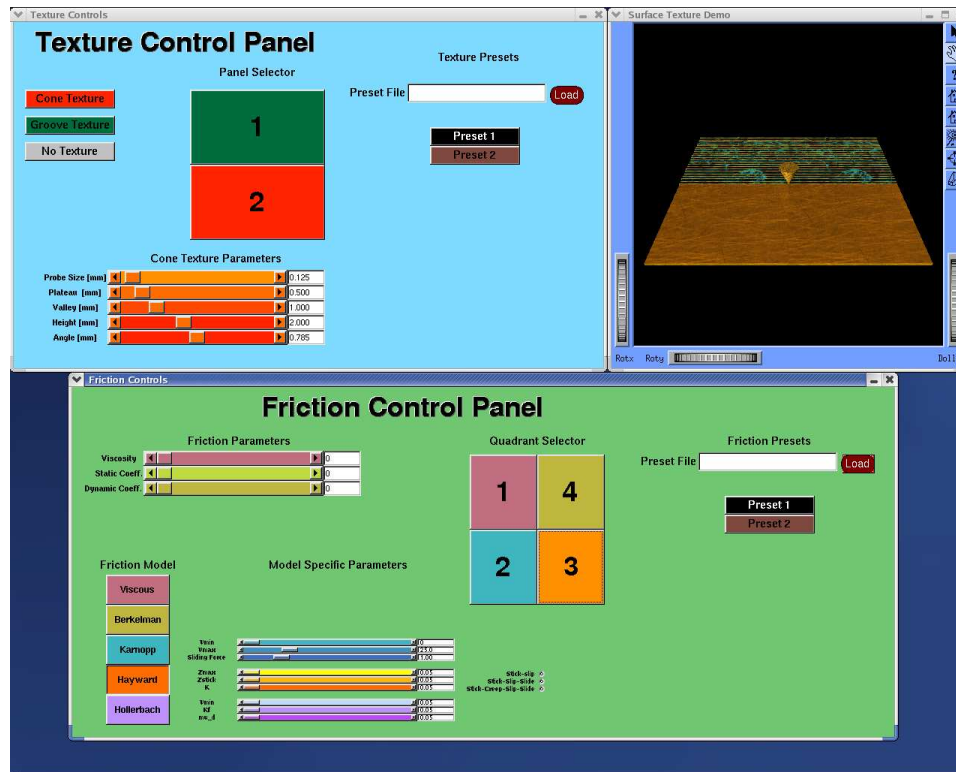
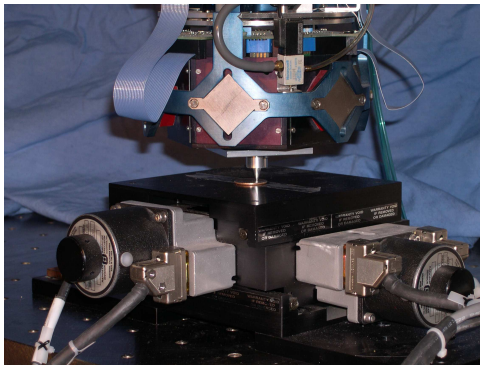


Figure 2.2: Screen shot of graphical interface for texture and friction prototyping.

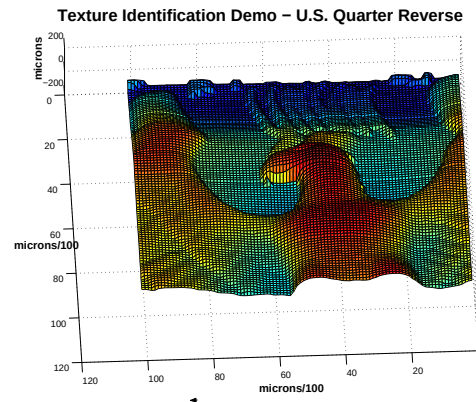
A graphical interface was developed for the haptic device which allows the prototyping of virtual texture model parameters quickly and easily (Fig. 2.2). The sliders seen in the figure can be used to modify texture and friction parameters which are placed on a selected panel or quadrant of the haptic display. It is thus possible to manipulate texture and friction independently. By placing different textures on side-by-side panels ready comparison of the effects of changing parameters can be made. While the interface displayed is used only for prototyping texture parameters and for demonstration purposes, its functionality is easily applied to designing psychophysical experiments.

Magnetic levitation devices such as the the IBM Magic Wrist or the MLHD used in this thesis can be used as force-feedback haptic systems, but it is also possible to make use of them as an input devices with which to measure force or position. Their fine position sensing capabilities make them capable of performing profilometry on fine surface textures. Figure 2.3 shows surface detail of a coin explored with a metal tip using the IBM Magic Wrist.

The MLHD has also been used as the master controller in a 12 DOF coarse-fine teleoperation system with bilateral force-feedback (see Fig. 2.4) [138, 139]. This system used the Magic Wrist as a slaved end-effector on a Unimation 560 PUMA arm. A deadband around the center of the



a



b

Figure 2.3: a.) Texture acquisition with surface profilometry measurements using the IBM Magic Wrist. b.) Surface details of American quarter obtained with Magic Wrist texture acquisition system.

wrist workspace allowed it to control the PUMA location. Inside the deadband, the MLHD and Wrist servoed to each other's location while outside of it the PUMA moved in rate control mode to try to reposition the wrist within the deadband. Since both Wrist and MLHD are floating, the motion of one is transparently visible to the other without the friction or backlash associated with mechanical linkages. This allows users to feel fine surfaces across an Ethernet link, potentially aiding manipulation tasks.

The MLHD has also seen use as a controller for microassembly with a minifactory [70], as a joystick with bilateral force-feedback controlling a 6-legged walking robot [130], and as a peg-in-hole simulation for comparing task performance in real and virtual environments [137, 140]. A description of its use as a texture synthesis tool follows.

2.2 Texture Simulation using the Constraint Surface Algorithm

One of the fundamental questions this thesis will address is how roughness perception is affected by the geometry of the probe-texture interaction. Namely, what happens to roughness perception if the contact between the texture surface and the haptic interaction point is modeled as something other than an infinitely small point.



a



b

Figure 2.4: a). IBM Magic Wrist b). IBM Magic Wrist mounted on PUMA 560 arm

Changing the probe geometry from an infinitely small point to an object that has some shape means that the haptic interaction point (HIP) at the center of the probe can no longer follow texture contours exactly but instead must follow a surface determined by the interaction of probe shape and texture geometry as seen in Chapter 4, Figure 4.3. This surface is used to control the position of the HIP as if it were at the center of a probe with some substantive shape (a spherical case is shown in Fig. 4.3). In this thesis, the surface followed by the HIP under these conditions is referred to as the constraint surface.

The constraint surface is composed of groupings of all the points for which the same motion constraints apply, a concept which is well known from the motion planning literature [99]. In practice, a set of parametric equations is used to indicate the desired height, z_{des} , of the HIP above the base plane of the texture (located at 0 on the z axis) given its current x and y coordinates.

The generalized constraint surface algorithm can be seen in Figure 2.5. During initialization of a texture, the (x, y) location of each element is stored in memory. From the flowchart it can be seen that the algorithm first finds the location of the HIP in the actual device workspace. Then, using the

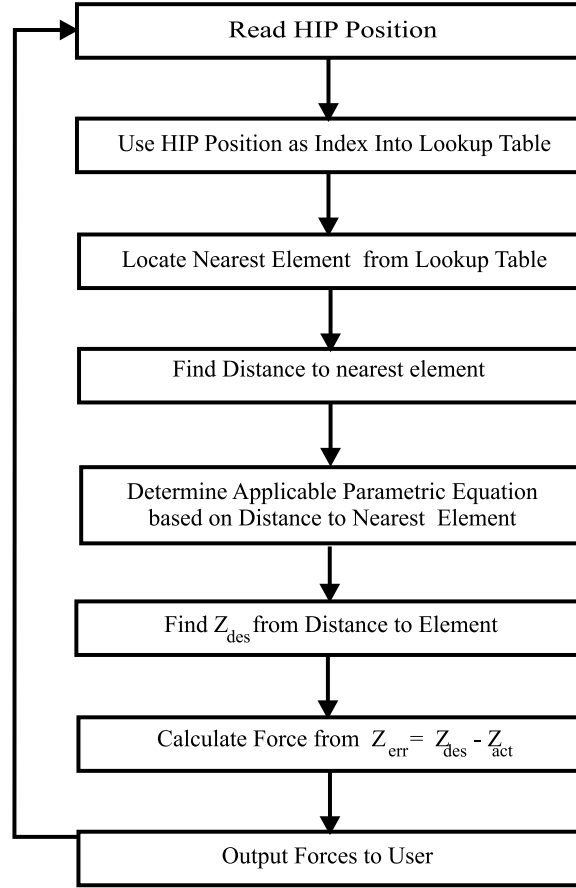


Figure 2.5: Flowchart for generalized constraint surface texture algorithm.

location of the HIP as an index into the stored memory containing element locations, it determines the nearest element to the HIP. The distance from the HIP to the element determines the parametric equation to be used in the calculation of the height of the constraint surface at that point, z_{des} . The difference between the desired probe height z_{des} , and the actual location of the point z_{act} , is the error signal z_{err} . The z_{err} value is used by a PD controller running at 1000 Hz to calculate the output force required to drive the position error to zero.

Haptic textures are thus generated from the constraint surface model as the MLHD manipulandum is moved through the device workspace. As a subject moves about the (x, y) plane, the manipulandum moves up and down vertically, its height depending on the geometry of the texture which is modeled beneath it. The simulation allows the manipulandum to lift completely free of the texture, either under user guidance or through interaction with model geometry.

It is important to note that the constraint surface model, as formulated, is a quasistatic model. That is to say that it assumes motions between control cycles will be very small. Under the

quasistatic model, the probe is regarded as effectively stationary at any given instant in time and dynamics are assumed to play no role in its behavior.

Three different constraint surfaces are used in this work. The first is based on the interaction of a spherical probe with a trapezoidal grating. This grating texture, with its sharp inflection points provides a contrast with the smoothly curved sinusoidal gratings used in Chapter 3.

The second constraint surface derives from a spherical probe and pseudo-randomly distributed truncated conical elements. This surface is intended to compare closely with real textures used by Klatzky *et al.* in psychophysical studies of indirect touch [66]. It will be used to assess the effects of probe size and compliance (see Chapters 5 and 7). It will also be used in conjunction with friction models to assess their effect on roughness perception (see Chapter 8).

When the probe shape is altered, the parametric equations governing HIP motion are also changed and a new constraint surface is generated. To assess the effects of probe shape on roughness, a third constraint surface, based on the interaction of an inverted conical probe and the dithered cones of the size experiments, is derived (see Chapter 6).

2.3 Roughness Magnitude Estimation

In roughness magnitude estimation experiments, subjects are asked to feel virtual textures with a manipulandum and make a numeric judgement of the roughness of the surface. During an individual trial, a texture spacing is explored while some level of the factor under study is applied. For example, during the dithered conical texture experiments, a single trial might consist of a texture spacing of 1.5 mm, explored with a 0.5 mm radius probe. Here, the factor under study is the radius of the probe and each probe-texture pairing is a trial. For other experiments, friction or compliance is the factor under study. In these experiments, a trial consists of a selected texture spacing, a probe size which remains invariant across trials, and a friction level which will vary from trial to trial.

2.3.1 Experimental Setup

Roughness magnitude estimation experiments were performed using subjects drawn from a student subject pool associated with the psychology department at Carnegie Mellon University and who received credit for participation. Additional subjects were paid and unpaid student volunteers from other departments and from within the Microdynamics Systems Laboratory at Carnegie Mellon.

Subjects are seated approximately 500 mm from a graphical display and keyboard used to enter roughness magnitude estimates. Textures are presented to the user's right hand by the MLHD manipulandum but no graphical representation of the texture is provided. Users listen to white noise via headphones during the entire experiment to prevent auditory identification of the texture roughness (Fig. 2.8a).

Subjects are informed that they will be presented with a variety of textures which they should explore with the MLHD manipulandum. No restrictions are placed upon the form of their exploration other than a warning that excessive force or banging will cause the device to shut down. They are also informed that the experiment will consist of a block of demonstration textures followed by a block of experiment textures. The demonstration block textures are representative of the range of experiment block textures that they will experience.

Certain experiments were blocked, with the blocks presented in counterbalanced fashion to prevent learning effects. In blocked experiments, each experimental block was preceded by a demonstration block, representative of the upcoming block's textures. Blocking was originally used to reduce variability in results. However, trial unblocked experiments indicated that subjects were consistent in their estimates across all trials. Unblocking allows comparison of magnitude estimate maximum values across all levels of the factor being studied. Thus later studies were performed as a single block, combining all factors randomly and preceded by a single demonstration block.

Subjects are told that they can explore any texture for as long as they wish within the overall time constraints of the experiment, which is limited to one hour. All subjects finished well within this time frame.

Subjects are asked to give a numeric estimate of the magnitude of the roughness of each of the experiment textures by entering a number on a computer keypad. They are told that they can assign roughness estimates to any positive range of numbers but that larger numbers are to reflect larger values of roughness and smaller numbers are to represent smaller values of roughness. They are specifically asked not to use 0 or negative numbers.

Each texture/factor level combination is presented to subjects a number, $n_{iterate}$, of times to reduce variability in magnitude estimation. If there are n_{space} element spacings and n_{levels} factor levels, then a subject explores $n_{trials} = n_{iterate}n_{space}n_{levels}$ trials in the course of an experimental run.

Demonstration block trials are presented in random order, as are experimental trials. This prevents learning effects.

Subject roughness estimates are recorded, along with the texture period and the level of the factor under investigation. Subjects are given feedback on trial number, via a graphical user interface, to ensure that they have actually keyed in a numeric estimate. MLHD manipulandum position and force data are recorded throughout the entire experiment at a 1000 Hz sampling frequency.

2.3.2 Determining the Psychophysical Function

The psychophysical function, $S = \Psi(I)$, is one of the basic measures used in this thesis to assess the effects of probe size, shape and compliance on texture perception. The process for determining $S = \Psi(I)$ involves obtaining numeric estimates of a subject's perception, S , of a stimulus, I , while at the same time recording the strength of the stimulus.

In this thesis, S will be the perceived roughness while the stimulus I will be considered the inter-element spacing of texture elements. If there are $k = 1, \dots, n_{space}$ different element spacings, a single experimental trial consists of a subject's numerical estimate of the roughness of the k th texture spacing and $S_k = \Psi(I_k)$. Three iterations of each trial are performed and averaged to obtain a single data point in the subject's psychophysical function for roughness, $\bar{S}_k = \bar{\Psi}(I_k)$.

Each subject's file contains separate records for each experimental trial. On subject debriefing, subjects occasionally report accidentally entering undesired values from time to time. This usually takes the form of keying in two estimates without hitting the <Return> key. As a result, occasional values in the data, (usually less than one per subject) are several orders of magnitude larger than expected and clearly do not belong to the range of roughness values used for all other textures. These outlier values, due to their large values, tend to skew results substantially, especially if normalization is used. Consequently, outlier removal is employed. Estimates are discarded if they were more than 10 times the median of all of the affected subject's estimates.

Magnitude estimation data were collected for all subjects in an experiment. MLHD position and force data were also collected for all subjects but not all were found to have useable data. This was due to a UDP communications glitch which resulted in occasional dropped command packets from the control computer to the MLHD controller. While this had no effect on subject data, it interfered with correct parsing of the MLHD data file, effectively corrupting it. Such experimental files were not analyzed and are not included in the psychophysical function's analysis.

If there are $i = 1, \dots, n_{subj}$ subjects in an experiment, a single subject's psychophysical profile, $S_i = \Psi(I_i)$, can then be described as the set

$$S_i = \{\bar{S}_1, \bar{S}_2, \dots, \bar{S}_{nsubj}\} \quad (2.1)$$

Each subject chose their own magnitude estimation scale with which to represent texture roughness. It seems highly unlikely that different subjects would place the same numeric value on textures with similar roughnesses (a phenomena, which if it existed, would have an analog in perfect pitch perception). It is necessary, therefore, to normalize the $S_i = \Psi(I_i)$ values across subjects, in order to make a useful comparison of the individual psychophysical functions. The normalized perception, $\hat{S}_i$ is obtained by dividing S_i by the mean of all estimates by subject i , M_{subj} , and multiplying by the mean of all estimates by all subjects in the experiment, M_{global} . Thus

$$\hat{S}_i = S_i \frac{M_{global}}{M_{subj}} \quad (2.2)$$

This normalization represents a scaling of the dependent variable by a constant and thus does not preserve its absolute magnitude. However, the normalization does preserve the location of events along the independent texture period axis as well as the curvature of the psychophysical roughness profile.

The normalized $\hat{S}_i$'s for a given condition level, c (*i.e.* probe size), are now combined across all subjects in the experiment to yield the cross-subject, normalized mean perception, $\bar{S}_c$ where

$$\bar{S}_c = \sum_{i=1}^{nsubj} \frac{\hat{S}_i}{nsubj} \quad (2.3)$$

Each experiment thus has a set of psychophysical functions determined for it. Each member of the set of functions corresponds to one level of the condition being tested (spherical probe radius, conical probe radius, *etc.*). For example, in the chapter on probe size (see Chapter 5), four spherical probes are used resulting in four different $\bar{S}_c = \Psi_c(I)$ functions.

For roughness perception, $\bar{S}_c = \Psi_c(I)$ is plotted on a log-log plot. This allows easy comparison with the literature where this kind of plot is common and also allows simple determination of b , the exponent in Stevens' power law (see Sec. 1.2.1) from the slope of any straight line in the plot. The exponent b can be useful for comparison with other authors' studies as well for comparison between experimental conditions in this thesis.

2.3.3 Measurement of Physical Properties Associated with Roughness

The physical properties which characterize texture roughness have yet to be determined. In this thesis, physical information is obtained by recording the forces, torques, position and orientation changes the MLHD's manipulandum experiences during individual experiment trials. As subjects explore a texture during a trial, force and position data are recorded at 1000 Hz. Recording at this frequency makes it possible to reconstruct events with frequencies up to 500 Hz. This frequency is well above the peak sensitivities for most of the skin's mechanoreceptors see Table 1.1 [154]).

As stated in Section 1.3, recorded position and force are used in this thesis to define a physical function, $P = \Phi(I)$ analogous to the psychophysical function $S = \Psi(I)$. $P = \Phi(I)$ relates the texture element spacings, I , to measures and statistical descriptions of physical properties, P , occurring during the exploration of the texture. Thus, for example, the mean acceleration during an experiment may be plotted as a function of element spacing, just as roughness is plotted against element spacing for $S = \Phi(I)$.

The process of obtaining an averaged $\bar{P}_c = \Phi_c(I)$ where $\bar{P}_c$ is the mean across subjects of the physical measure for a single experimental factor (*i.e.* probe radius), is identical to that used for finding $\bar{S}_c = \Psi_c(I)$ but does not involve the normalization step.

For each subject and each experimental trial, the physical measure or descriptive statistic is first obtained. Then, within-subject averaging over trial iterations occurs. Outlier removal occurs at this stage, with outliers in the data more than 10 times the median value removed. This is done so that statistical analysis can be performed. Finally, the measure is averaged across subjects but not normalized. This produces the function $\bar{P}_c = \Phi_c(I)$ which can then be correlated with $\bar{S}_c = \Psi_c(I)$.

While a correlation between $\Phi_c(I)$ and $\Psi_c(I)$ does not, strictly speaking, imply causality, this thesis will regard it as strong evidence that the physical property $\Phi_c(I)$ underlies the perceptual chain that ends with $\Psi_c(I)$.

2.4 JND for Roughness

The JND for roughness, in terms of texture element spacing, was determined for three experimental factors: spherical probe radius, conical probe radius and probe/texture compliance. In each of these experiments, the texture geometry was that of dithered truncated cones (see Sec. 5.2 for details). A variant of Kaernbach's unforced weighted up-down JND staircase technique was used for this experiment, as described in Section 1.2.1 [60, 84].

Kaernbach’s technique presents users with two stimuli and asks subjects to select the one perceived as more (or less) intense. In this thesis, the stimulus will always be considered to be texture element spacing while the perception is one of roughness intensity. One of the two stimuli is held constant during a JND determination and will be referred to here as the base texture spacing (BTS). The other stimulus is changed as the JND is determined and is referred to as the comparison texture spacing (CTS).

Kaernbach’s technique assumes that the stimuli are monotonically related to perceived intensity. Based on this assumption, an answer that the larger stimulus is more intense is correct, while all other answers, including the “Don’t Know” option are considered wrong. A correct answer yields a decrease in the difference, δ_{stim} , between the BTS and CTS, $Step_{corr}$, while an incorrect or unsure answer yields an increase in this difference, $Step_{incorr}$ or $Step_{unsure}$ respectively (see Sec. 1.2.1).

Selection of the initial CTS and step sizes are somewhat empirical since too large a CTS or too small a step size will lengthen the JND determination process substantially. Empiric pre-testing showed that an initial CTS of 150% of the BTS and an initial $Step_{corr}$ of 10% of the initial δ_{stim} produce rapid convergence on a steady-state JND. $Step_{incorr}$ and $Step_{corr}$ derive from $Step_{corr}$ as explained in Section 1.2.1.

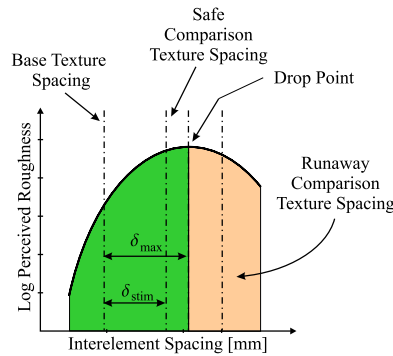


Figure 2.6: Using the drop point to decide base texture spacing. If the comparison texture spacing is larger than the drop point (light-colored zone) a runaway JND may occur.

The selection of the BTS’s is problematic since the psychophysical function for roughness perception is not monotonic. Rather it is roughly quadratic-shaped with perceived roughness increasing along with inter-element spacing up to a maximum, and then decreasing again [66]. The peak of the roughness function is related to the drop point (DP), the texture spacing at which the probe would just fall between the elements (see Fig. 2.6).

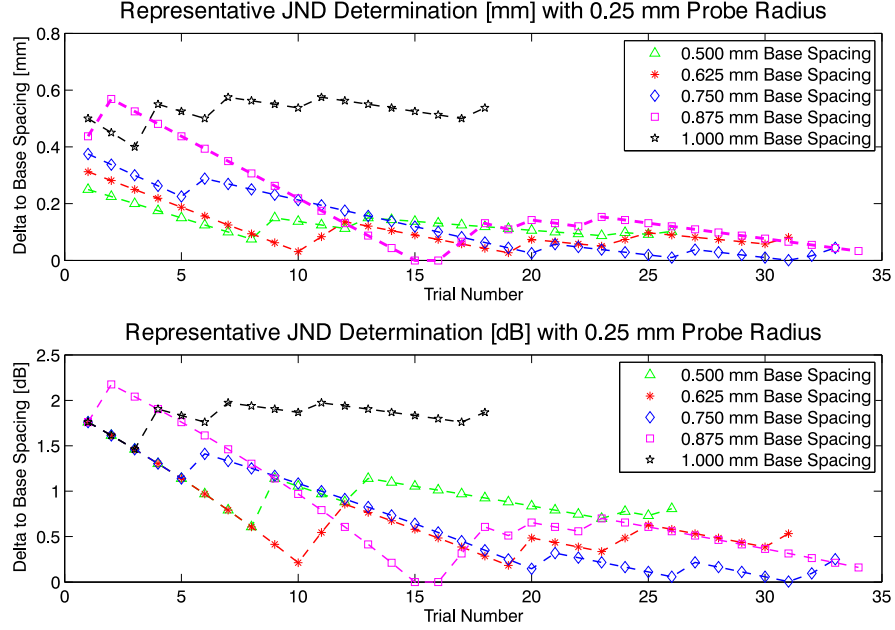


Figure 2.7: Determining JND using unforced weighted up-down adaptive threshold estimation. JND determinations for five base texture spacings are shown. The track for a base texture spacing of 1.00 mm may represent a runaway JND.

The JND algorithm assumes that increasing element spacing results in a rougher perceived surface, *i.e.*, that the CTS spacing will stay on the ascending limb of $\Psi(I)$. Thus δ_{stim} will decrease as the CTS moves towards the BTS. If δ_{stim} is increased so that the CTS moves beyond the drop point and onto the descending limb of $\Psi(I)$, roughness will now be perceived as decreasing with increasing element spacing, violating the initial assumption and resulting in a “runaway” JND (see Fig. 2.7). The runaway occurs because subjects now perceive larger spacings as smoother and never answer “correctly”, resulting in greater and greater δ_{stim} ’s. The largest difference between CTS and BTS, δ_{max} , is therefore restricted by the DP. This sets an upper bound on the maximum BTS spacing. The initial CTS is 150% of the BTS. Thus the largest BTS possible must keep CTS less than δ_{max} or $DP/1.5$.

The DP’s from [66] were used to set the upper bounds on BTS for probe radii ranging from 0.25-1.0 mm. A universal lower bound for BTS of 0.4 – 0.5 mm (depending on experiment) was chosen to stay well within the MLHD’s resolution capabilities. Between upper and lower bounds the range was divided into 3-5 equidistant BTS’s. For experiments in which the factor being studied

was spherical or conical probe radius, 3 probe radii (0.25, 0.5 and 1.0 mm) were used. For the compliance experiment 3 levels of compliance were used (5, 10 and 15 N/mm). The experiment was divided into 3 blocks, each block representing either a single probe radius or level of compliance crossed with all BTS's for that experiment. The blocks were presented to subjects in a counterbalanced order. The total number of JND's determined per subject for one experiment was therefore 9-15 depending on the number of BTS's used.

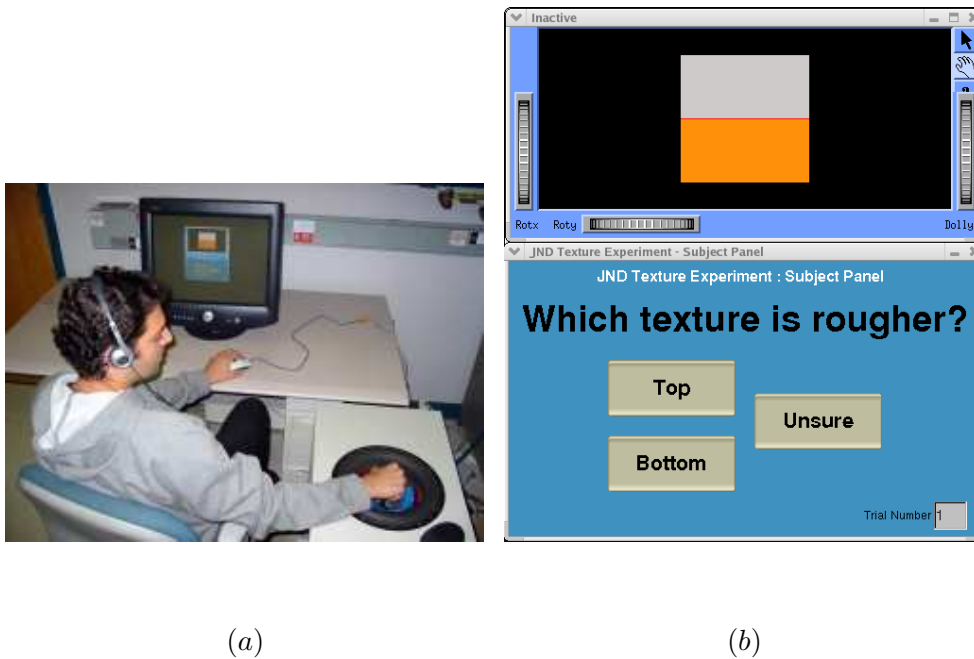


Figure 2.8: a.) Subject using the magnetic levitation haptic device during JND experiments. b.) JND experiment subject panel with selection buttons and visual active panel display.

During a JND trial, the subject was presented with two textures on vertically adjacent panels (Fig. 2.8a). During a trial, a panel was chosen at random for display of the BTS. A CTS was placed on the other panel. Subjects were asked to feel both panels using the haptic probe and state if the top panel was rougher than the bottom. They were allowed to answer with “Yes,” “No,” or “Don’t Know.” As stated above, it was assumed that the rougher panel would correspond to larger spacings. A colored visual display indicated the panel on which the probe was located (Fig. 2.8b). No other feedback was provided. Subjects listened to white noise using headphones to prevent auditory identification of textures.

Each subject determined a JND for each experimental factor level (probe radius or compliance) and BTS pairing. The JND determinations of a representative block for a single subject can be seen in Fig. 2.7. A block requires a variable but large number of comparisons between CTS and BTS.

In conclusion it should be noted that adaptive JND experiments would be nearly impossible with physical texture plates since the number of stimuli needed would be prohibitive. The rapid changes in stimuli needed for the experiment would also be very difficult to perform with physical texture plates but are straightforward with virtual textures.

Chapter 3

Sinusoidal Textures and Point-Probes

3.1 Introduction

Psychophysical investigations of texture perception are only rarely performed using virtual textures generated by a haptic device. This is largely due to the limited quality of virtual texture which can be produced. Haptic device characteristics, such as stiffness and position bandwidth, are usually inferior to their real world counterparts, casting doubt on the validity of any psychophysical results. Indeed, virtual psychophysical findings frequently conflict with those determined with real textures [68].

Several previous studies use a sinusoidal model of texture as their basis [68, 107, 148]. This model is simple to generate and manipulate. Subjects use an infinitely small point-probe to explore a sinusoidal texture wave that has some fixed spatial frequency (see Fig. 3.1) and are then asked to estimate the roughness of the sinusoidal texture.

These studies show that subjects vary considerably in the way in which their roughness perception is related to sinusoidal texture frequency. Roughness perception is found to depend on the individual subject; some subjects report increased, and others decreased, roughness with decreasing texture frequency. This suggests that roughness perception of the same texture is inherently different from one person to the next. The claim has been made that the variations in individual psychophysical responses, when taken in aggregate, produce a quadratic function which is an artifact of lumped analysis [68].

Another possible explanation of inter-subject perceptual variability is that it occurs because subjects have difficulty in differentiating between texture periods. The haptic device used to produce the texture may be limited in its ability to produce discernably different textures because of its

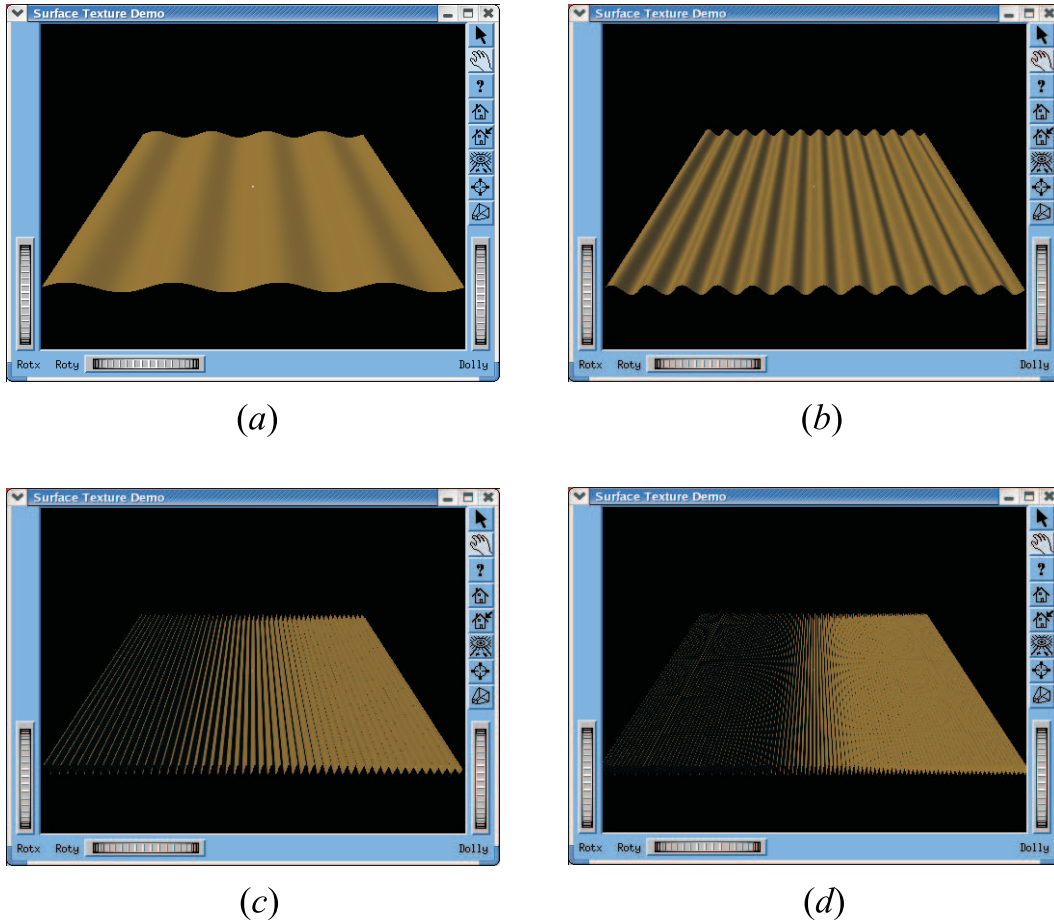


Figure 3.1: Graphic representation of four examples of sinusoidal grating texture used for psychophysical experiments with a (a). 6mm period, (b) 2 mm period, (c) 0.50 mm grating and (d) 0.25 mm grating.

operating characteristics. For example, a device with low stiffness might make all textures feel “soft” and this could result in highly variable reported roughness.

It is also possible that the sinusoidal model fails to capture some fundamental aspect of real textures which produce quadratic perception curves. The inter-subject differences in perception could result from the failure of the model to account for texture geometry, probe size, probe shape, compliance or frictional effects.

In order to investigate the discrepancies noted by others between real and haptic textures, it is necessary to examine how roughness is perceived when an infinitely small probe is used to explore virtual sinusoidal gratings. The haptic device used in this thesis is the Carnegie Mellon magnetic levitation haptic device (MLHD) which has state-of-the-art operating characteristics including high stiffness, high position bandwidth and fine position and force resolution (See Sec. 2.1). While no

haptic device can perfectly simulate the stiffness and resolution of the real world, the MLHD should be capable of rendering texture significantly better than the devices employed in previous studies.

Examination of individual roughness magnitude estimates together with multi-subject aggregate findings should reveal whether or not inter-subject variability is the cause of the inverted “U”-shaped psychophysical function seen when lumped roughness perception data are plotted against texture period.

This baseline set of roughness perception experiments with sinusoidal gratings will also allow comparison with similar experiments that investigate how the addition of size, shape and compliance to a virtual probe alters roughness perception.

3.2 Experimental Design

Sinusoidal gratings (see Fig. 3.1) with spatial periods ranging from 0.025 to 6.00 mm were haptically generated using a penetration depth algorithm. The periods were selected to cover a range which, at its lower end, approached the resolution of the MLHD and at its upper end allowed for 4 spatial cycles within the workspace of the device. A total of 33 different periods were used, with the period space being more heavily sampled at lower frequencies to provide more nearly even sampling when the data was plotted logarithmically.

The psychophysical function’s form has been noted to vary between subjects in other studies [68]. One possible cause may be that subjects have different levels of sensitivity to roughness and the functions may be centered at different element spacings as a result. The chosen range of periods expands the lower end of the range of periods studied by others [68] to allow detection of this possible shift.

The amplitude of the sinusoid was chosen to be 0.4 mm peak-to-peak, to conform to the height of the dithered conical elements investigated by Klatzky *et al.* in [66] and in later sections of this thesis.

The haptic probe is considered to be an infinitely small point. When the probe is in contact with the surface, a force is generated, proportional, and opposed to, the penetration depth along the z axis. The orientation of the manipulandum is controlled to keep it vertical at all times. When the probe is not in contact with the surface it is allowed to fly freely, experiencing no forces other than those required to control its orientation and counteract gravity.

A total of 27 subjects completed this experiment. The subject pool and experimental setup was identical to that described in the earlier experimental design section (Sec. 2.3.2). The experiment used only one probe size, a point, and was unblocked, with the various sinusoidal periods randomly presented

The experiment used 7 demonstration textures which spanned the range of 33 experimental texture periods and included its extremes. The demonstration textures were each presented only once, in random order, prior to the start of the actual experiment. The demonstration allowed subjects to get an understanding of the device and the range of textures which they are about to feel.

The 33 textures in the actual experiment were each presented to a subject 4 times, yielding a total of 132 magnitude estimation trials.

Subject roughness estimates were recorded, along with the texture period and MLHD gain settings. MLHD manipulandum position and output force data were recorded throughout the entire experiment at a 1000 Hz sampling frequency.

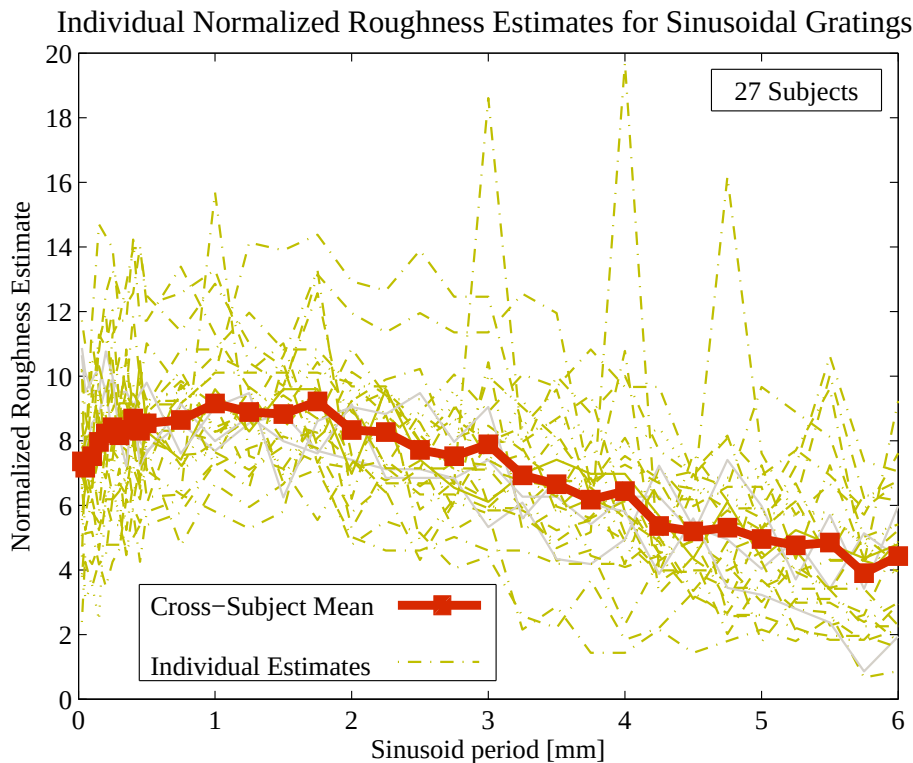


Figure 3.2: Plot of individual normalized roughness psychophysical functions for 27 subjects superimposed on their cross subject mean. There is a significant effect of spacing on roughness estimates ($F(32,726)=11.5273, p<0.0001$).

For this experiment the MLHD proportional gains were set to nominal values of 10 N/mm in translation and 25 Nm/radian for orientation. This provided a relatively stiff surface and prevented, to a large extent, rotation of the manipulandum. Only z-axis forces were actively generated by the penetration depth algorithm and rotation was not desired. Derivative gains for the MLHD were set to 0.04 N/mm/s in translation and 0.5 N/radian/s for orientation to prevent instability. A feedforward force, which reduced the weight of the flotor to approximately 0.69 Newtons, was also applied.

3.3 Sinusoidal Texture and Roughness Perception

Magnitude estimation data were collected for all 27 subjects. MLHD position and force data were also collected for all 27 subjects but only 23 subjects were found to have useable data. This was due to the UDP communications glitch mentioned above (Section 2.3.2).

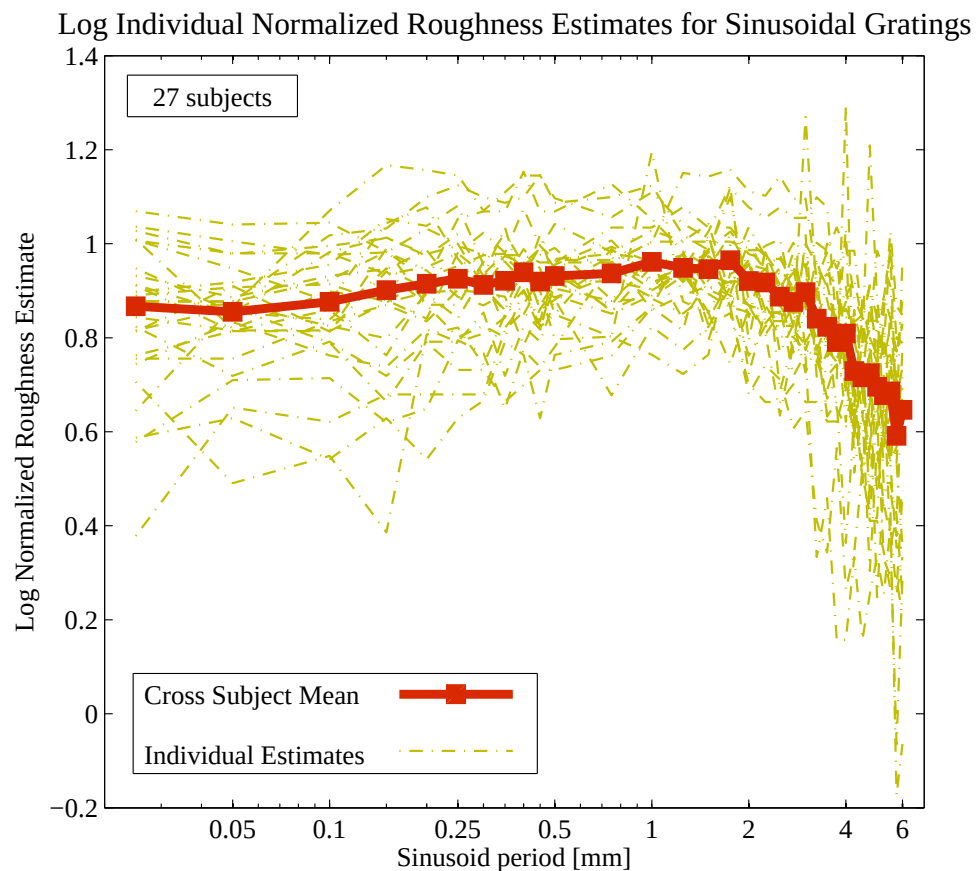


Figure 3.3: Log plot of the of individual normalized roughness psychophysical functions for 27 subjects superimposed with the log of their cross subject mean.

Each subject's file contained 132 separate records, one magnitude estimation for each texture encountered. Outliers with values greater than ten times a subject's overall median response were removed.

The psychophysical function $S_i = \Psi(I_i)$ was calculated for each subject and the overall psychophysical function $\bar{S} = \Psi_{Sine}(I)$, was found by averaging the normalized individual functions, following the techniques outlined in Section 2.3.2.

Superimposed plots of $S_i = \Psi(I_i)$ for each subject as well as the mean roughness function ($\bar{S} = \Psi(I)$) can be seen in Fig. 3.2. It is obvious that, though the functions show considerable variance between individual subjects, most follow a pattern of an initial rise followed by a long decline in roughness as a function of increasing texture period. A one-way ANOVA shows that element spacing has a significant effect on the roughness perception ($F(32,726)=11.52$, $p < 0.0001$).

A log-log plot allows us to observe the details of the function at lower periods, as seen in Fig. 3.3. Here it can be seen that over the initial range of 0.0625-2 mm in period, there is actually very little change in roughness. At a period of approximately 2 mm, the roughness appears to decline rapidly. It seems possible that two different texture perception processes are at work, the first causing the high, but relatively invariant, roughness estimates for periods up to 2 mm and the second resulting in the steady decline of perceived roughness for periods larger than 2 mm.

Dividing the psychophysical function into those estimates for texture periods less than, and those greater than, 2 mm, it is possible to find the individual slopes of these two divisions. The early, flat division has a mean slope of close to zero (see Table 3.1) with subjects' function slopes having different signs. In the later, descending division, subjects' functions exhibit a fairly wide range of negative slopes but only two subjects showed slopes with positive signs. The overall log-log slope for periods of greater than 2.0 mm is approximately -0.8, virtually identical to the Stevens' power law exponent, b , determined by Kornbrott *et al.* [68].

Texture Period Range [mm]	Mean slope	Median	σ	Maximum	Minimum	# Positive/Negative
0.025-1.75	0.067	0.041	0.118	0.328	-0.160	20/7
2.25-6.0	-0.823	-0.703	0.676	0.084	-2.775	2/25

Table 3.1: Slope of roughness function in a log-log plot for small sinusoid periods (0.025-1.75 mm) and large sinusoid periods (2.25-6.0 mm).

The reasons for the bipartite behavior of roughness estimates on sinusoidal gratings is unclear. One possibility is that the magnitude of the perceived texture's underlying physical properties is relatively constant below a 2 mm period but declines above 2 mm. In this case the physical function, $S = \Phi(I)$, should correlate with roughness perception; it should show a flat or slightly rising slope below a 2 mm period and a more steep, descending slope above it.

A second explanation for the bipartite behavior is that it is a function of texture sensing or processing by the subjects. For example, it is possible that, for small period sinusoidal gratings, the neural sensing elements of the finger and hand are saturated and thus unable to discern changes in the physical properties exciting them. The roughness function might therefore be expected to follow the changes in physical properties over the range of large period sinusoids but fail to follow the physics generated by smaller period gratings. These two hypotheses will be tested below in Section 3.4. In this section the position and force data from the MLHD captured during magnitude estimation trials will be examined to determine how probe position, velocity and acceleration change with spacing. The degree to which physical properties such as power or kinetic energy correlate with subject roughness estimates will also be determined.

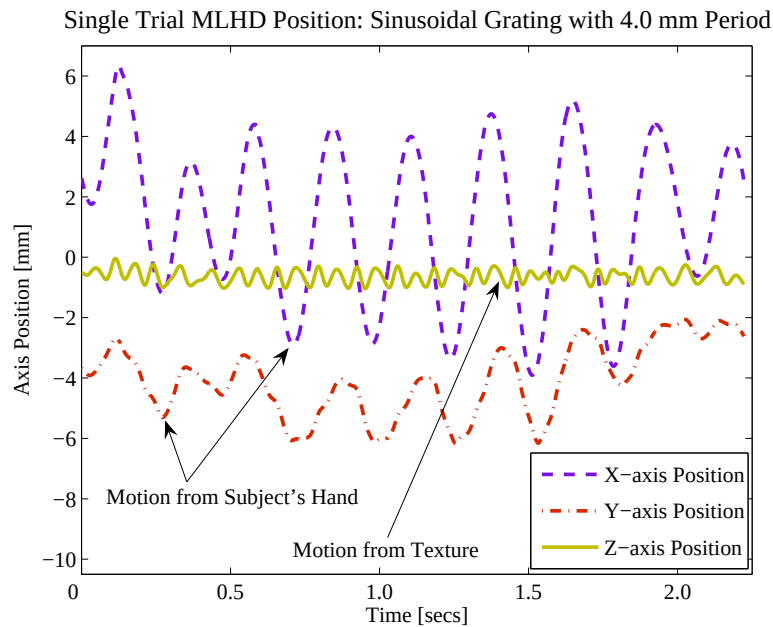


Figure 3.4: Magnetic levitation haptic device manipulandum position during a single roughness magnitude estimation trial using a sinusoidal grating with a 0.4 mm peak-to-peak amplitude and a 4 mm spatial period. The trial is approximately 2.2 seconds in duration

Figure 3.4 shows the position of the haptic device manipulandum during a single trial. The large sinusoidal motions along the x axis are due to subjects' hand motion as they explore the textured surface. While the dithered texture is isotropic, with the ridges of the sinusoidal grating oriented along the y axis, the major component of most subjects' hand motion was found to be along the x axis. This represents a hand motion along a right-left axis from the perspective of the subjects, a direction which is the most kinematically natural, given their seating position, with the device on their right. The smaller sinusoidal motions along the y axis, whose frequency is the same as the x -axis motion, demonstrates that subjects did not align their motion exactly along the x axis, instead moving at an angle to it. The difference in phase between x - and y -axis motion is due to a slight arcing motion of the manipulandum, as the hand sweeps it across the texture.

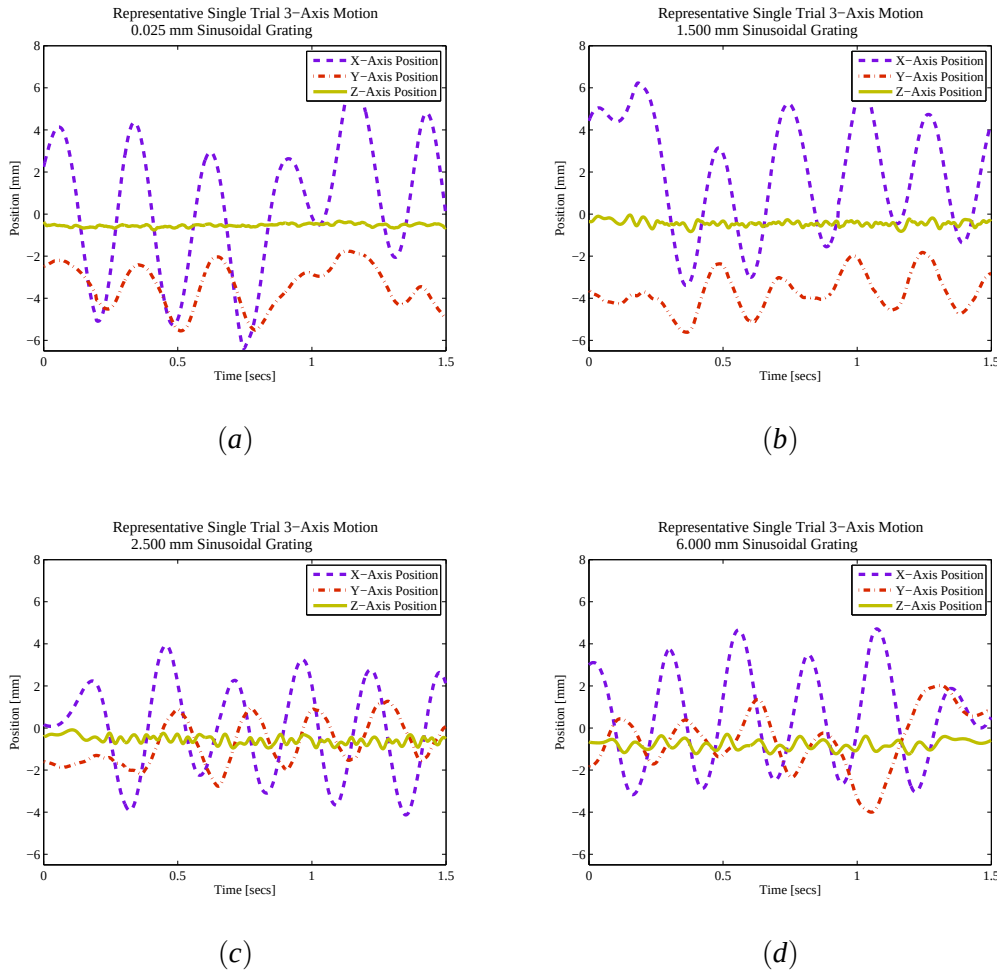


Figure 3.5: Representative example of manipulandum motion along x , y and z axes during a single subject trial on sinusoidal grating texture with a period of a.) 0.025 mm. b.) 1.5 mm, c.) 2.5 mm and d.) 6.0 mm.

The small amplitude motion in the z axis has a frequency which differs substantially from x - and y -axis motion (see Fig. 3.4). Z -axis motion is determined by the interaction between the subject's hand, the device, and the texture algorithm presented. In this experiment a sinusoidal pattern with an amplitude determined by the constraint surface algorithm (CSA) might be expected if the HIP precisely followed the textured surface. Examining Fig. 3.5 it can be seen that this is clearly not the case, especially for sinusoids with small periods. There are several reasons for the z -axis path to deviate from a pure sinusoid.

First, as in all experiments in this thesis, the HIP was not constrained to stay on the texture surface; subjects might elect to lift it above the texture or it could fly above the surface due to dynamic effects.

Second, the position of the HIP is determined by a penetration depth algorithm. The depth of penetration is determined by the force applied by the subject, which may vary with time and hand position. The penetration depth effect is readily apparent since the mean z -axis position is usually offset downwards from zero by the weight of the subject's hand.

Third, device resolution and frequency response may prevent accurate haptic display of the required position. The MLHD has been modeled as a second order spring damper system using measurements of the MLHD's damping and spring coefficients (see Section 2.1). The frequency response has a ± 3 dB corner at approximately 120 Hz with slow roll off. This will lead to attenuation of the MLHD's position-following capabilities when the device is required to rapidly traverse sinusoidal gratings with small periods. Figure 3.6 shows representative examples for a single subject of z -axis position over a 1 second interval for a wide range of sinusoid periods. It is evident that the amplitude of the sine wave is smallest for the shortest periods (those ≤ 0.5 mm).

Representative Sinusoidal Texture Grating Z-Axis Motion for 32 Period Lengths

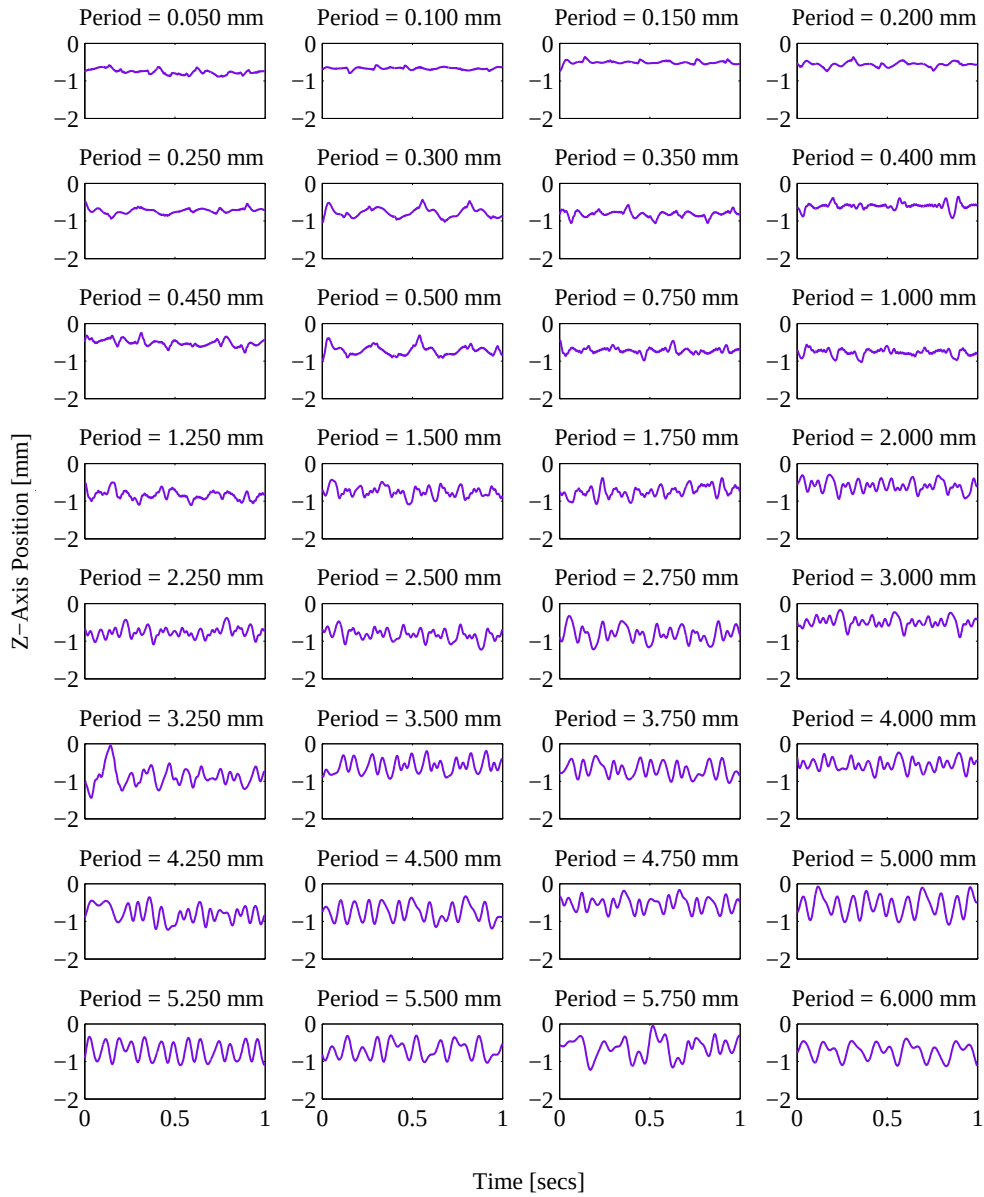


Figure 3.6: Representative example from a single subject of z -axis motion for periods ranging from 0.05 mm to 6.0 mm.

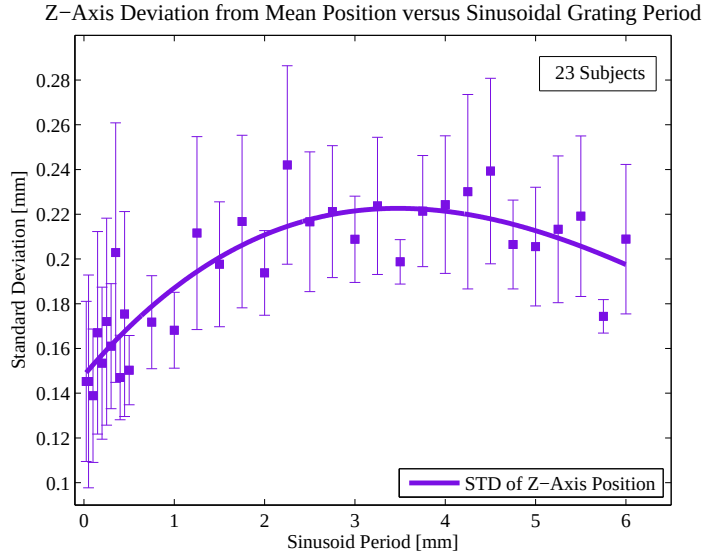


Figure 3.7: The mean over all subjects of the standard deviation of z -axis position (power) as a function of sinusoidal grating period. A one-way ANOVA shows no significant effect of spacing on power. A third order fit to the data with $R^2 = 0.76$ is also shown.

If the standard deviation (σ) of the z -axis position waveform is plotted against sinusoid spatial frequency, as in Figure 3.7, it can be seen that σ , equivalent to the waveform's power, increases with period. The overall range of σ is approximately 0.1 mm, 25% of the 0.4 mm peak-to-peak amplitude commanded by the sinusoidal texture algorithm. While σ 's range is small and variation between subjects is large, the trend shows the attenuation of power at high spatial frequencies. This is what is expected due to limited device position bandwidth.

The temporal frequency with which texture elements are encountered by a subject is directly related to the velocity of the probe as it moves across the surface. Figures 3.8 and 3.9 show the velocity along and about each axis as a function of sinusoid period. Angular velocities are negligible and, as expected, do not vary with period since the device is constrained in rotation. The mean velocity across subjects, for the x and y axes, is independent of period. The x -axis velocity is of particular interest, since the sinusoidal grating is oriented with its ridges perpendicular to the x axis. Taking a subject's actual mean x -axis velocity during each trial and dividing it by the corresponding trial's sinusoidal period determines the ideal temporal frequency at which a subject will encounter sinusoid peaks. Averaged over subjects, this yields a plot of ideal temporal frequency versus sinusoid period (see Fig. 3.10).

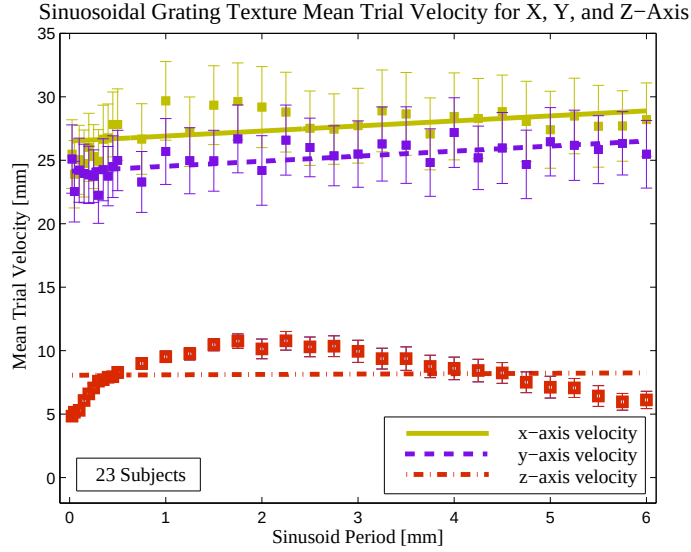


Figure 3.8: Cross subject mean trial velocity as a function of sinusoidal grating period with linear fits for x , y , and z axes.

The ideal temporal frequency plotted against sinusoid period can be almost perfectly fit by a straight line with a slope of -0.98 in a log-log plot (Fig. 3.10 (b)). If subjects maintain a constant x -axis velocity, V_x , regardless of texture period, el_T , then Fig. 3.10 is the expected shape of the temporal frequency ($f = V_x/el_T$) curve.

It must be kept in mind that these are ideal temporal frequencies which assume that subjects move with constant velocity along the surface, never lifting above it, and that the MLHD is capable of producing, accurately, the range of frequencies required.

Since the device is being servoed at 1000 Hz and data is being sampled at 1000 Hz, the Nyquist Rate implies that, for the smallest periods encountered, the ideal frequencies (> 500 Hz) are larger than those the device can accurately reproduce. Indeed, with a 120 Hz -3 dB corner for the device, any period ≤ 0.2 mm will suffer significant attenuation. This does not have an apparent effect on roughness estimates; roughness for sinusoid periods less than 0.2 mm is judged to be high and appears to be as intense as the roughness experienced by subjects between 0.2 and 2.0 mm. For periods greater than 0.2 mm, the device should be capable of following a sine wave without significant attenuation.

These findings demonstrate the importance of using a high-resolution, high bandwidth haptic device for texture simulations. This thesis finds a power law exponent for textures with large

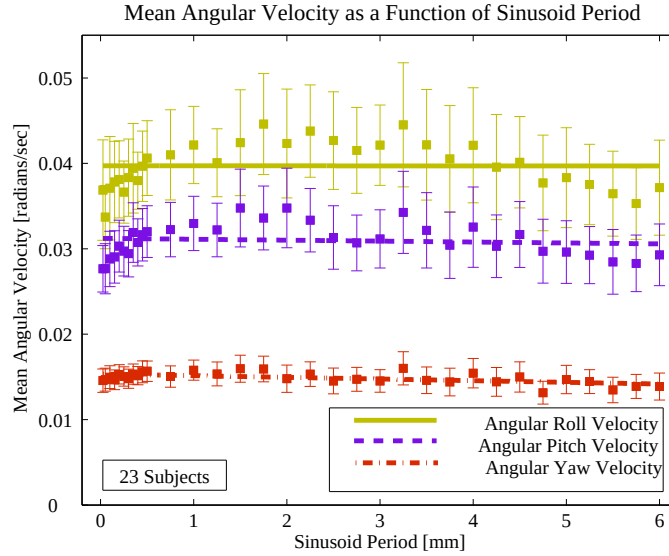
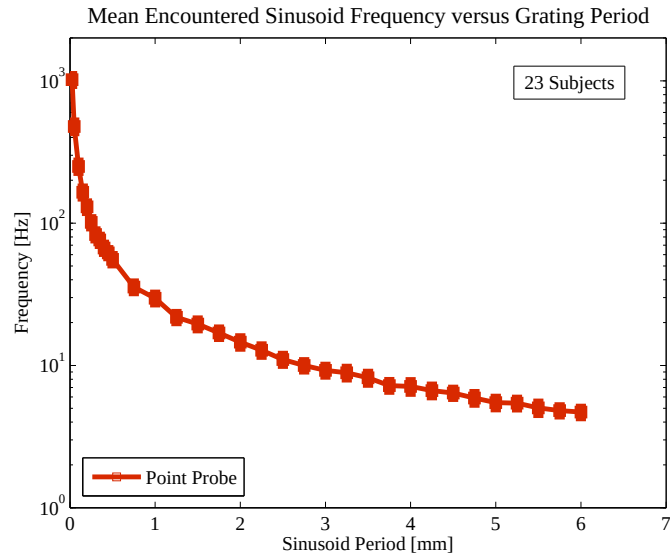
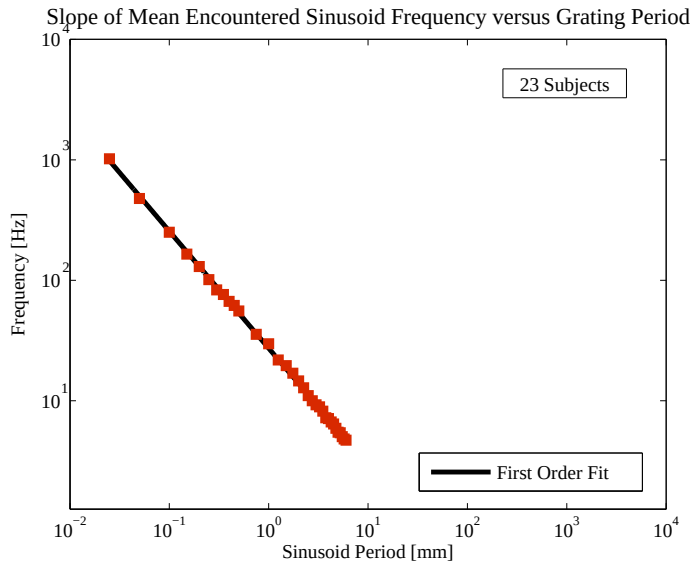


Figure 3.9: Mean angular velocity for roll, pitch and yaw in radians/second. A linear fit is plotted to each set of data. There is no significant effect of sinusoid period on roll, pitch or yaw angular velocity.

(>2 mm) element spacings which correlates well with previous studies. It seems evident, however, that a device, such as a PHANTOMTM, with a position bandwidth of only 50 Hz [19], will produce attenuated textures for spacings below this size. Such attenuated textures may be responsible for anomalous results found by some authors. Certainly, other researchers have found the PHANTOMTM to be limited in its ability to render accurate textures [16, 22].



(a)



(b)

Figure 3.10: (a). Semilog plot of temporal frequency (mean over subjects) encountered by subjects versus sinusoidal grating period. Temporal frequency is calculated as a subject's mean x -axis velocity divided by the sinusoidal grating period. (b). Log-log plot of temporal frequency encountered by subjects versus sinusoidal grating period with first order fit. Slope = -0.977 ± 0.008 , Y-intercept = 1.372 ± 0.051 , $R^2 = 0.99$

3.4 Physical Properties Underlying Roughness Perception

It seems clear that the sensation of roughness results in some way from manipulandum motion which in turn is governed by the texture and probe geometry. At present, the physical properties of motion which result in a sensation of roughness are poorly understood. It is possible that factors relating to roughness may be integrated over time by texture receptors in the hand [48, 88] or they may be related to specific frequency information [7]. Studies of vibratory sensation indicate that for frequencies between 5 and 50 Hz, Fast Acting receptors of type 1 (FA1's) are responsible for detecting vibration while for higher frequencies, FA2's are the receptor. While these receptors respond to motion in a particular frequency band, the physics of their interaction with a hand-held manipulandum is not well understood. For example, it is thought that the FA2's response results from an integration of vibrational power over time [5, 6]. Since it is possible to measure the motion of the haptic device while a subject explores a texture, it seems reasonable to try to correlate the physics of device motion with the subject roughness estimates.

There are several potential physical properties which might be sensed as roughness by the receptors in the hand. It is, for example, possible that changes in position alone might elicit a response from receptors and result in a sensation of roughness. That is, a simple deflection of the skin through some distance might be interpreted as roughness. This seems unlikely, since the receptors related to texture respond best to changing stimuli, rather than long term deformation. Empiric observation of tool-based texture exploration demonstrates the need for motion on the part of the probe in order to experience roughness. A second, more likely, cause of roughness sensation is the change in position of the probe against the skin with respect to time. One such measure of changing position is probe velocity.

3.4.1 Velocity and Roughness

Looking back at Figure 3.8 it can be seen that mean absolute instantaneous x -axis and y -axis velocities, determined from the first derivative of position recordings, are unrelated to sinusoid period and are effectively constant. X -axis and y -axis motion was not constrained during the experiment, allowing the subjects to freely explore the surface in these directions. Thus, x -axis and y -axis velocity are almost entirely related to subject input and not influenced by the texture geometry. As shown in Figure 3.9, the angular velocities about the x , y and z axes are likewise uninfluenced by the sinusoid period. Since the motion of the HIP was constrained to prevent rotation, this is not

surprising. A 1-way ANOVA revealed no effect of sinusoid period on the velocity along or about any axis except z (see Table 3.2).

Velocity	F	p
x -axis	(32/726)=0.2667	> 0.05
y -axis	(32/726)=0.2225	> 0.05
z -axis	(32/726)=7.1575	< 0.001
Roll	(32/726)=0.2611	> 0.05
Pitch	(32/726)=0.3055	> 0.05
Yaw	(32/726)=0.2281	> 0.05

Table 3.2: 1-way ANOVA results for effect of sinusoid period on manipulandum linear and angular velocity. Only z -axis velocity shows a significant effect.

Since roughness perception of sinusoidal texture is clearly affected by period, it is logical to discount the possibility that velocity in any axis other than z carries roughness information. Examining the relationship of mean z -axis velocity to sinusoid period more closely (see Fig. 3.8) it is noted that the velocity function increases rapidly with increasing period, then decreases more slowly over the rest of the period range. The roughness function follows a similar pattern, peaking slightly earlier. A third order fit to the velocity curve fits well ($R^2 = 0.96$) as does the third order fit to roughness ($R^2 = 0.97$) (Fig. 3.11).

Comparison of z -axis velocity with subject roughness estimates (see Fig. 3.11) shows similarities in the shape of the two fit curves. The slope of a straight line fit to the linear ascending portion of the roughness data is 2.08 mm/s per millimeter of period (mm/s/mm_{period}). A similarly fit line for the velocity curve has a slope of 4.64 mm/s/mm_{period}. The linear fits to the descending portions of the two curves show even greater similarity with a descending slope of -1.23 and -1.24 mm/s/mm_{period} for roughness and velocity respectively. It seems that z -axis velocity is related to texture roughness perception since changes in sinusoid period induce similar changes in both factors. This seems especially true for sinusoidal textures with periods of greater than 2.25 mm.

Some differences between roughness and velocity functions do exist. For example, the maximum roughness (of the fitted curve) is found at a texture period of 1.39 mm while the texture period at maximum velocity is higher, at 2.10 mm. It is also of note that for the smallest texture periods the roughness is greater than for the largest periods while the reverse is true for velocity. Since

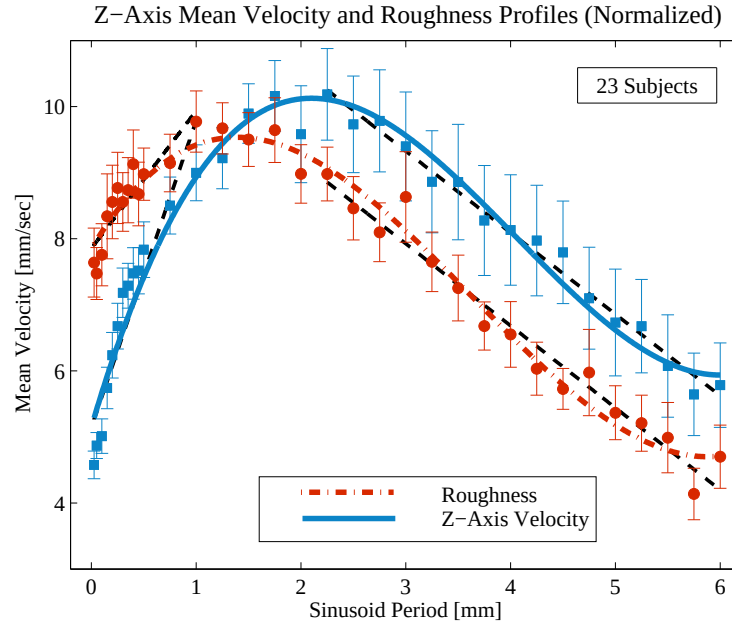


Figure 3.11: Cross subject mean trial velocity and normalized subject roughness estimates as a function of sinusoidal grating periods. A third order fit to each complete data set is shown. ($R^2=0.97$ and 0.95 for roughness and velocity respectively). A linear fit to the data is also shown for small periods of $0.025-1.00$ mm and for large periods of $2.25-6.0$ mm. (Ascending Roughness Fit $R^2 = 0.80$, Ascending Velocity Fit $R^2 = 0.87$, Descending Roughness Fit $R^2 = 0.9599$, Descending Velocity Fit $R^2 = 0.99$.)

a one-to-one relationship between roughness and velocity does not exist, it is possible that, while velocity itself does not characterize roughness, some related factor might.

3.4.2 Kinetic Energy and Roughness

Many receptors for senses other than touch respond to energy. For example, the cones in the eye respond to light energy in specific ranges of wavelengths. Since motion of the haptic manipulandum imparts motion to the skin of the hand and thus to the touch receptors, it is possible that mechanoreceptors are responsive to the amount of kinetic energy in that motion. In Figure 3.12 a plot of kinetic energy as a function of sinusoid period can be seen, along with a plot of subjects' roughness estimates at the same periods. A 1-way ANOVA showed a significant effect of sinusoid period on mean kinetic energy ($F(32,726)=7.62$, $p < 0.001$). The kinetic energy, KE , for a mass, m , moving with velocity, v , is typically calculated as

$$KE = \frac{mv^2}{2}. \quad (3.1)$$

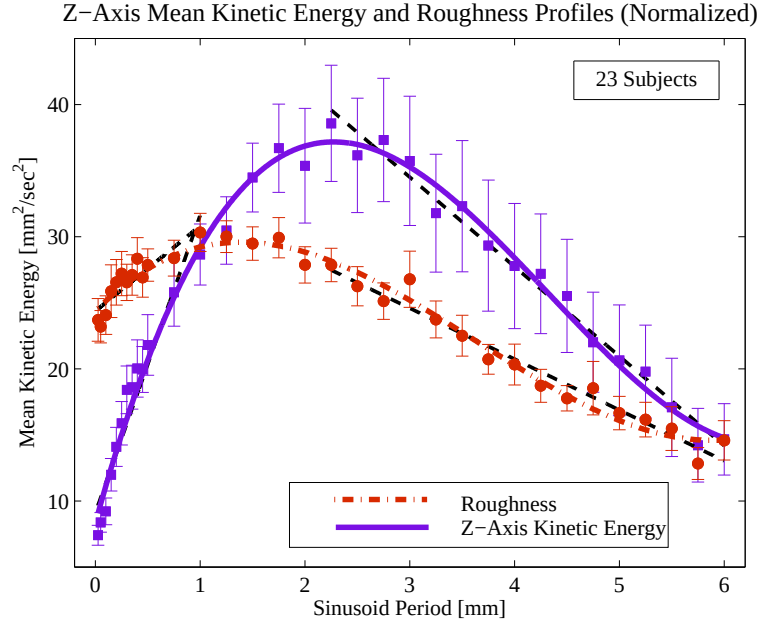


Figure 3.12: Mean z -axis kinetic energy compared to roughness as a function of sinusoid period. Energy and roughness are normalized for comparison. A third order fit to each data set is shown with $R^2 = 0.99$ for the kinetic energy and $R^2 = 0.97$ for roughness. A linear fit to the data is also shown for small periods of 0.025-1.00 mm and for large periods of 2.25-6.0 mm. (Ascending Roughness Fit $R^2 = 0.80$, Ascending Velocity Fit $R^2 = 0.93$, Descending Roughness Fit $R^2 = 0.96$, Descending Velocity Fit $R^2 = 0.98$.)

The moving mass, in this case, comprises the mass of the flotor. This is a constant (581 grams) and thus has no effect on the shape of the curve defined by kinetic energy as a function of element period, $\Phi(I)$. The KE curve's shape is a function of v^2 alone. Squaring velocity changes the slope of the curve but does not effect the position of the maximum. The slopes of straight lines fit to the ascending portion of the roughness and kinetic energy curves are 6.45 and 22.5 $\text{mm}^2/\text{s}^2/\text{mm}_{\text{period}}$ respectively. Lines fit to the descending portion of the curves have slopes of -3.85 and -6.78 $\text{mm}^2/\text{s}^2/\text{mm}_{\text{period}}$ respectively.

While the velocity function appears, on inspection, to be close to the shape of the roughness function, simply shifted in phase, the kinetic energy function differs from that of roughness substantially. The slope of its linear portions are dissimilar and it is no closer in phase to the psychophysical function for roughness than the velocity function. Kinetic energy, has therefore, been rejected as the underlying physical factor which results in a perception of roughness.

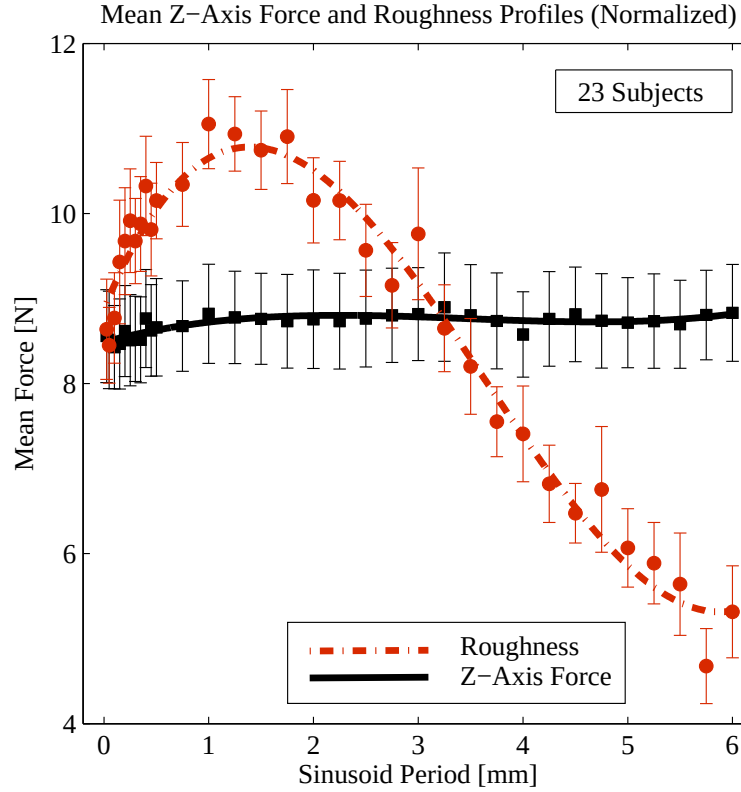


Figure 3.13: Mean z -axis force compared to roughness as a function of sinusoid period. Force and roughness are normalized for comparison. A third order fit to each data set is shown with $R^2 = 0.70$ for force and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows no effect of sinusoid period on mean z -axis forces ($F(32,726)=0.049, p=> 0.05$).

3.4.3 Acceleration and Roughness

Another possible physical property that might account for roughness perception is the force the haptic device exerts on the subject's fingerpads. Since the MLHD's manipulandum position is recorded at 1000 Hz while subjects render roughness estimates, it is possible to compute its second derivative and determine its instantaneous acceleration. Acceleration is related to force by $F = ma$. The mass of the manipulandum is constant and the assumption is made that the user applies a relatively constant force to it (consisting of the weight of their arm and hand plus applied muscular force). Thus acceleration is a measure, albeit a noisy one, of the resultant forces experienced by the subject. The assumption of constant subject-applied force is given some justification by noting that texture period has no significant effect on mean force measurements as shown in figure 3.13.

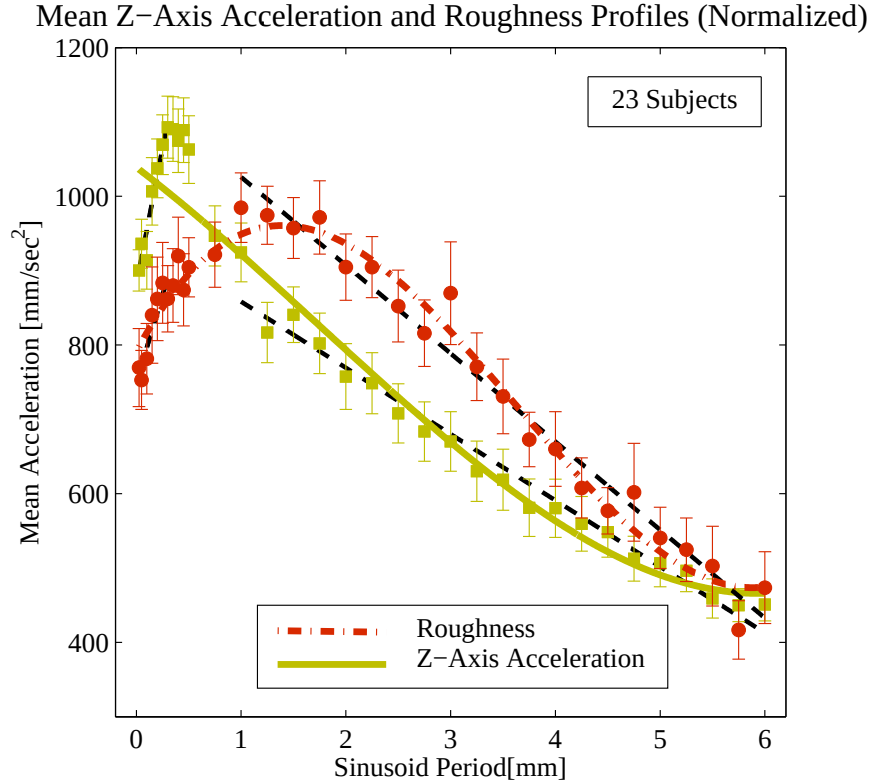


Figure 3.14: Mean z -axis acceleration compared to roughness as a function of sinusoid period. Acceleration and roughness are normalized for comparison. A third order fit to each data set is shown with $R^2 = 0.94$ for acceleration and $R^2 = 0.97$ for roughness. A linear fit to the data is also shown for small periods of 0.025-0.3 mm and for large periods of 1.0-6.0 mm. (Ascending Roughness Fit $R^2 = 0.85$, Ascending Acceleration Fit $R^2 = 0.93$, Descending Roughness Fit $R^2 = 0.97$, Descending Acceleration Fit $R^2 = 0.97$.)

A plot of mean z -axis acceleration, normalized to subject roughness estimates, is shown in figure 3.14. A clear relationship between roughness and mean instantaneous acceleration can be seen although acceleration shows a much sharper peak at a much smaller texture period than that of roughness. The maximum acceleration occurs at a period of 0.3 mm as measured from the data, while roughness peaks at 1.39 mm using the third order fit. The slopes of the nearly linear ascending portions of the function differ by nearly a factor of two (730.8 and $470.3 \text{ mm/s}^2/\text{mm}_{period}$ for acceleration and roughness respectively) but are nearly the same for the linear fits to the descending portions (-89.1 and $-118.6 \text{ mm/s}^2/\text{mm}_{period}$ for acceleration and roughness respectively).

It seems likely that acceleration is related to roughness perception in some way, especially for textures with larger periods. It is also possible that some other physical property related to acceleration characterizes roughness, and acceleration itself is only a secondary characteristic.

3.4.4 Force and Roughness Perception

While the acceleration function shows some similarities to that of perceived roughness, the dissimilarities are large enough to suggest that it is inadequate to characterize roughness completely. If acceleration is taken as a metric of the instantaneous force felt by the hand, then force must bear some complex non-linear relationship to texture roughness perception.

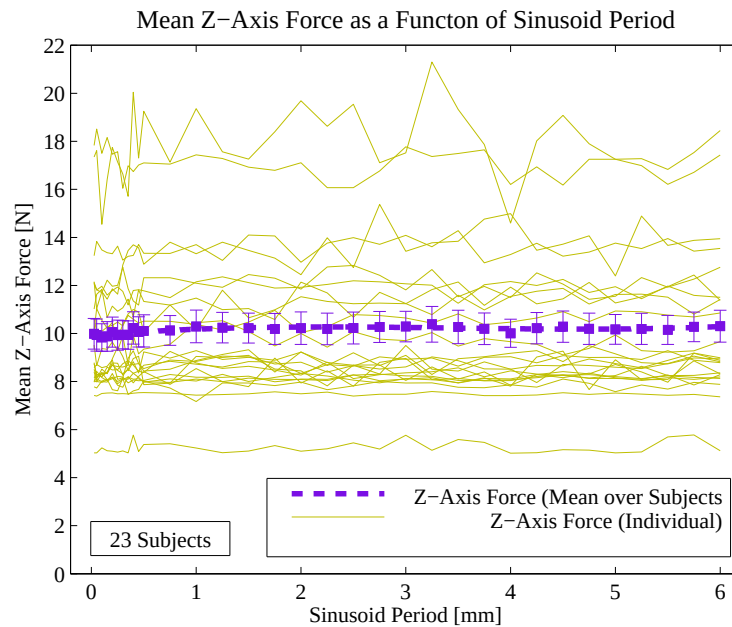


Figure 3.15: Mean of z -axis force over time during trials at a range of different sinusoid periods. Each line represents individual subject mean z -axis forces over the range of periods. The average over subjects of the mean z -axis force at each period is also shown. There is no significant effect of spacing on the mean absolute z -axis force.

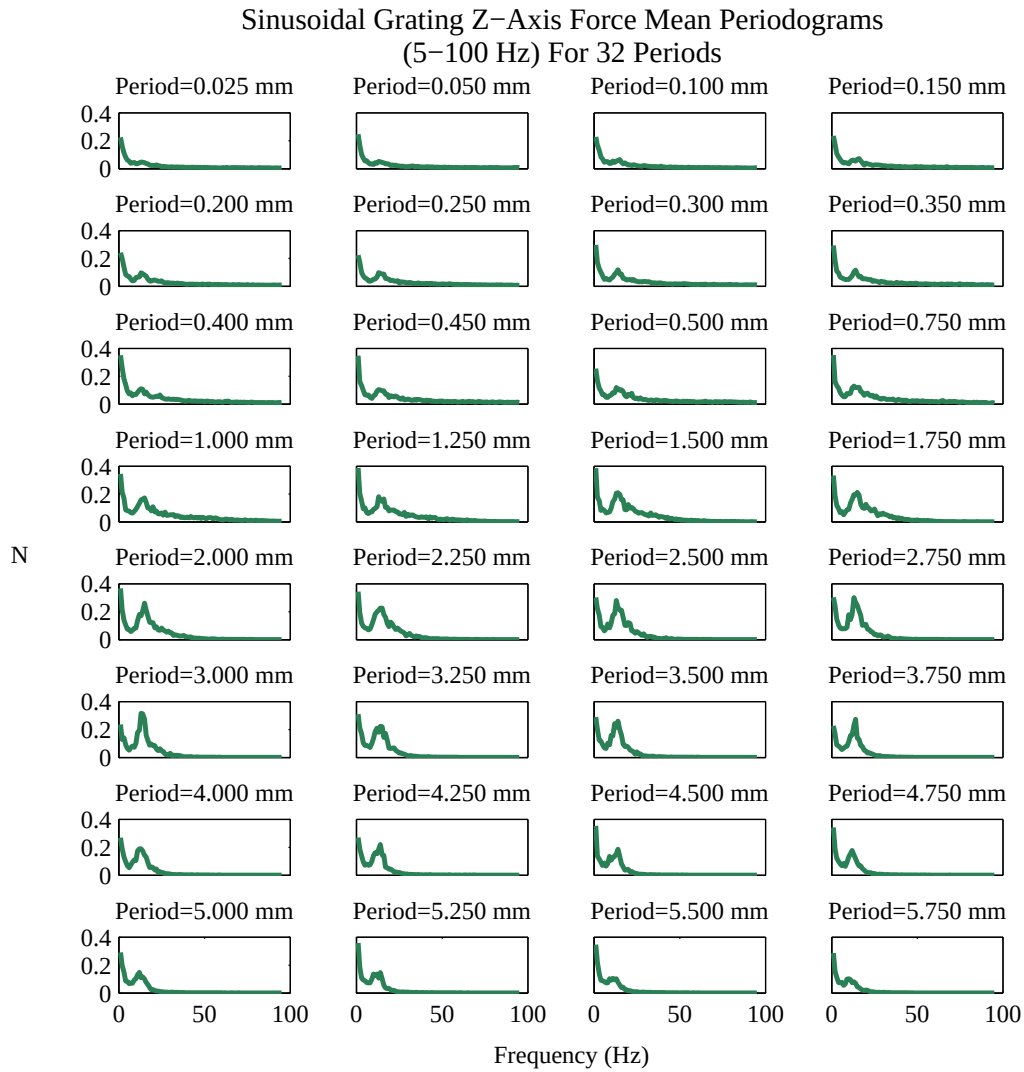


Figure 3.16: The z -axis force signal power spectral density periodograms for sinusoidal texture periods of 0.025–5.75 mm. Each periodogram is found using a 1024 sample Fast Fourier Transform. The mean of the PSD periodograms over subjects and trial iterations is shown for frequencies from 5–100 Hz.

It is also possible to look directly at the forces produced by the MLHD during the subject roughness magnitude estimations trials (see Fig. 3.15). These forces are generated by the device in response to the depth of penetration of the HIP below the texture. As a result, the maglev forces are the commanded forces and not necessarily the actual forces felt at the fingertips that might be measured if a force sensor was placed between them and the manipulandum. The observed force, averaged across subjects, is approximately 10 Newtons and includes a feed-forward force of 5 Newtons (reducing the weight of the flotor from approximately 580 grams to 70 grams). A plot of the mean z -axis force shows no significant effects from sinusoid period and mean force remains effectively unchanged throughout the range of texture periods investigated. It is interesting to note that while mean acceleration shows a significant effect of sinusoid texture spacing, commanded force does not. The reason for this may be that, while mean force measures the average amount of force applied during a trial, mean acceleration yields a measure of the average instantaneous force, or force variability experienced by subjects.

It is possible that force itself, is the physical parameter used to carry roughness information about a surface to the subject's fingertips via the haptic probe. If this is the case then the force signal's power (its variability) should correlate with the roughness felt by subjects. Since the receptors in the fingertip have specific ranges of roughness to which they are sensitive (see Section 1.2.2), the signal power in a receptor's responsive frequency band should correlate with roughness if that receptor is responsible for sensing roughness.

The two receptors most likely to be responsible for roughness perception are the FA1 and FA2s (Meissner's and Pacinian Corpuscles respectively). The FA1 receptor has a frequency range of approximately 5-50 Hz while the FA2 is specialized to respond to frequencies above 50 Hz (See Table 1.1) [59, 154]. Since the maglev commanded force is sampled at 1000 Hz the Nyquist frequency limits the useful examinable signal to 500 Hz. Taking the power spectral density (PSD) of the force signal using a periodogram technique with 1024 Fast Fourier Transform points, yields a PSD periodogram for frequencies ranging from 1-500 Hz. In Figure 3.16 the mean of periodograms over subjects and iterations for each sinusoidal period can be seen. These periodograms show the power spectral density of the force signal for a frequency range of 5-100 Hz. This range is selected since the FA touch receptors show little activity below 5 Hz while above 100 Hz, the signal power is very small. It is interesting to note that most of the power in the signal seems concentrated in the band from 5-30 Hz regardless of texture period. The total power seems to increase to a peak around the

2-3 mm sinusoid texture period and then decline gradually. This suggests that the total power in the force signal may be the salient physical factor perceived as roughness.

The area under the entire PSD periodogram produces a measure of the total power of the force signal. This measure is only an approximation for total power since the actual range of frequencies generated may exceed 500 Hz. Most of the power in the PSD signal, however, is actually found below 100 Hz (see Fig 3.16).

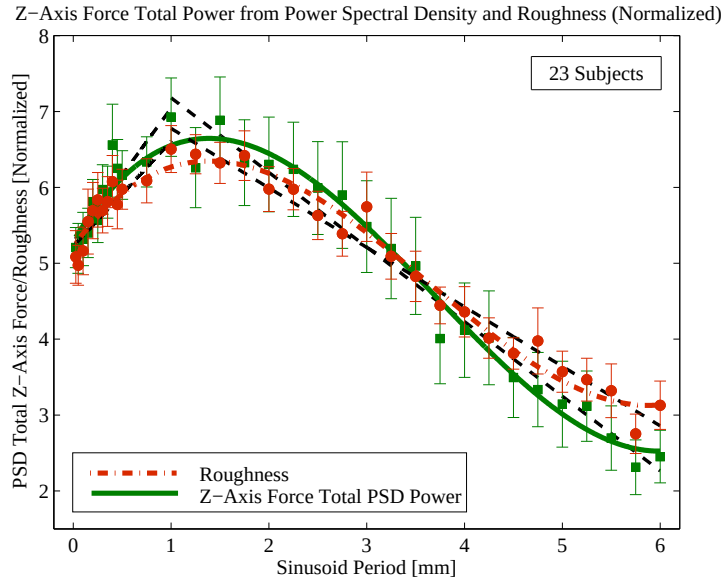


Figure 3.17: Total power of z -axis force signal from the power spectral density compared to roughness as a function of sinusoid period. Power and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum of $1.39 \text{ mm}_{\text{period}}$ and $R^2 = 0.98$ for force power and a maximum of $1.39 \text{ mm}_{\text{period}}$ and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on power in the z -axis force signal ($F(32,726)=7.5761, p= 0.00$). A linear fit to the initial (< 1.0 mm texture period) and final (> 1.0 mm texture period) portions of each curve with slopes as follows: Ascending Power= $1.76 \text{ N/mm}_{\text{period}}$, $R^2 = 0.83$, Ascending Roughness= 1.38 , $R^2 = 0.80$, Descending Power= $-0.98 \text{ N/mm}_{\text{period}}$, $R^2 = 0.97$, Descending Roughness= -0.78 , $R^2 = 0.97$.

A plot of the total power in the PSD periodogram for all sinusoidal texture periods, averaged over subjects, can be seen in figure 3.17 together with the psychophysical roughness function. The curves are normalized to each other to eliminate scaling factors. The two curves are virtually identical, supporting the conclusion that the total signal power of force is the key physical determinant of roughness. The maximum roughness and maximum force signal power occur at exactly the same texture period (1.39 mm) while the slopes of linear fits to the ascending and descending portions

of the functions are very similar, particularly, in the descending limb (1.76 and 1.38 N/mm_{period} ascending and -0.98 and -0.78 N/mm_{period} descending for power and roughness respectively).

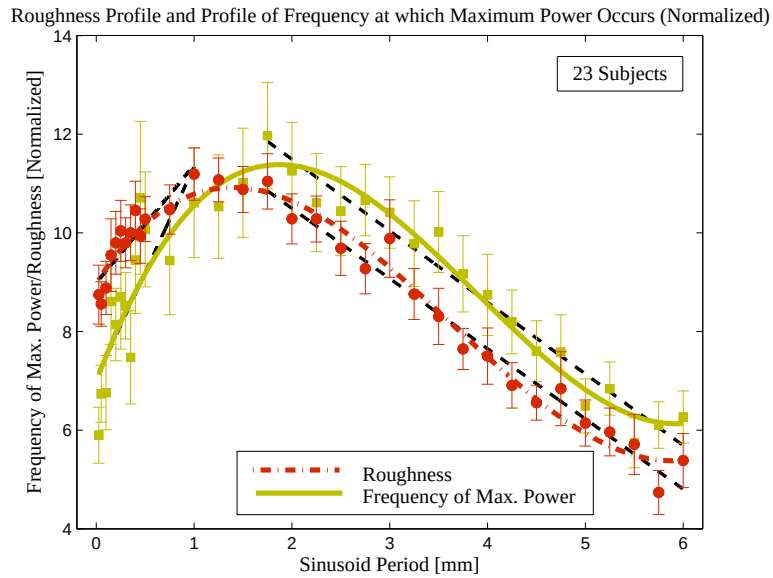


Figure 3.18: Roughness estimation function compared with the frequency at which the maximum z -axis force signal, as measured by the power spectral density, is found. Frequency and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum at 1.88 mm_{period} and $R^2 = 0.89$ for frequency and a maximum at 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on the maximum frequency of the z -axis force signal ($F(32,726)=4.2232$, $p=0.00$). A linear fit to the initial (< 1.0 mm texture period) and final (> 1.75 mm texture period) portions of each curve with slopes as follows: Initial frequency= 4.28 Hz/mm_{period}, $R^2 = 0.63$, Initial Roughness= 2.38, $R^2 = 0.80$, Final frequency= -1.45 N/mm_{period}, $R^2 = 0.96$, Final Roughness= -1.42 , $R^2 = 0.97$. Outliers greater than 10x the mean over subjects were removed from the frequency data.

The total power can be seen as a measure of the variability of the force to which a subject's fingers are exposed as they move the manipulandum across a textured surface. This might explain why mean instantaneous acceleration correlates moderately well with roughness since it, too, provides a measure of the variability of force. Instantaneous acceleration is subject to significant noise since it is determined from the second derivative of position. Noise in the position signal is amplified by the derivation process and may result in significant error in the acceleration values, particularly in the high frequency range of the spectrum. It would therefore be reasonable to expect that high frequency textures, which produce high frequency acceleration changes, would be least accurately represented by acceleration and therefore have the poorest correlation with roughness estimates.

This appears to be the case as the acceleration function matches roughness well for larger period textures but poorly for low period textures.

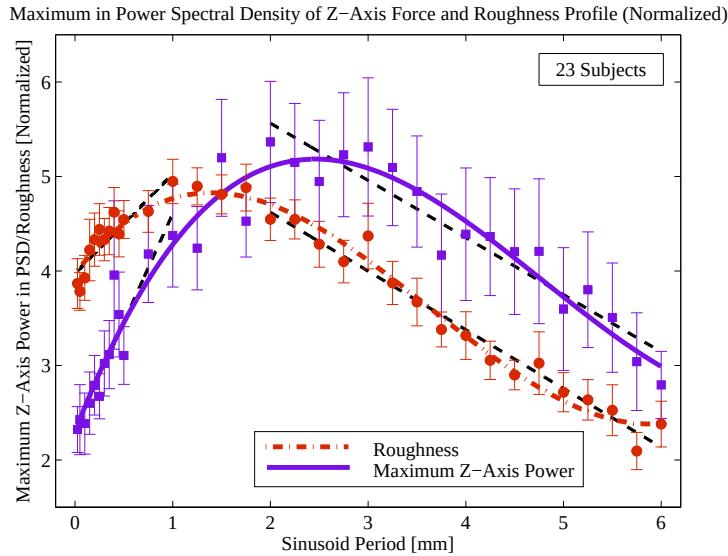


Figure 3.19: Roughness function compared with the maximum z -axis force signal, as measured by the power spectral density. Maximum force and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum at $2.45 \text{ mm}_{\text{period}}$ and $R^2 = 0.93$ for frequency and a maximum at $1.39 \text{ mm}_{\text{period}}$ and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on maximum z -axis force signal power ($F(32,726)=3.1514$, $p < 0.001$). A linear fit to the initial ($< 1.0 \text{ mm}$ texture period) and final ($> 2.00 \text{ mm}$ texture period) portions of each curve with slopes as follows: Initial PSD= $2.29 \text{ N/mm}_{\text{period}}$, $R^2=0.86$, Initial Roughness= 1.05 , $R^2 = 0.80$, Final PSD= $-0.61 \text{ N/mm}_{\text{period}}$, $R^2 = 0.91$, Final Roughness= -0.62 , $R^2 = 0.97$. Outliers greater than 10x the mean over subjects were removed from the PSD data.

An interesting question to ask at this point is whether or not the force signal determines roughness solely as a function of its power or whether or not the frequency of the signal affects roughness perception. It is possible that some function of the force signal frequency maps to roughness perception. Examining the frequency at which the PSD periodogram contains the most power, $freq_{max}$, it can be seen that this frequency rises and falls in correlation with roughness perception (see Fig. 3.18). The maximum force found in the PSD periodogram with respect to sinusoidal texture period (see Fig. 3.19) demonstrates that the maximum force is also moderately correlated with roughness estimates. The maximum force reaches a peak at a sinusoid period of approximately 2.45 mm and has a declining slope virtually identical to that of roughness perception. It is possible that subjects are determining surface roughness based on $freq_{max}$, linearly relating frequency

to roughness but it is more likely that both the maximum force signal and the $freq_{max}$ signal are coupled to the texture surface geometry in the same way and therefore trend up and down in tandem. The similarity in terminal slope and the location of the peak of both $freq_{max}$ and maximum force at texture periods higher than that of roughness, imply that frequency and maximum force are coupled. It is, furthermore, possible that maximum force is merely a metric for mean force signal power, measuring the strength of the maximum's deviation from the mean. Thus $freq_{max}$ may be a surrogate measure of the power in the force signal.

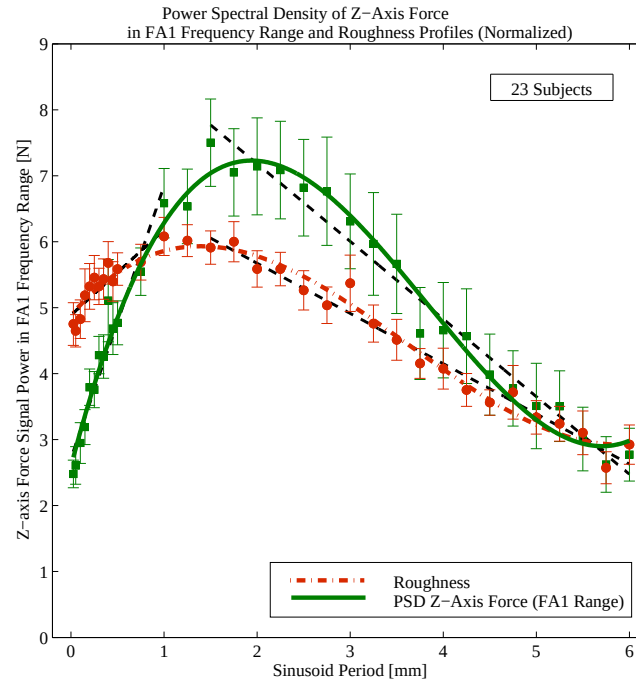


Figure 3.20: Power Spectral Density of z -axis forces within the FA1 receptor frequency range (5-50 Hz), compared to roughness as a function of sinusoid period. PSD and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum of 0.94 mm_{period} and $R^2 = 0.97$ for PSD and a maximum of 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on FA1 z -axis force signal power ($F(32,726)=7.7873$, $p < 0.001$). A linear fit to the ascending ($< 1.0 \text{ mm}$ texture period) and descending ($> 1.5 \text{ mm}$ texture period) portions of each curve with slopes as follows: Ascending PSD= $4.12 \text{ N/mm}_{period}$, $R^2 = 0.93$, Ascending Roughness= 1.29 , $R^2 = 0.80$, Descending PSD= $-1.17 \text{ N/mm}_{period}$, $R^2 = 0.97$, Descending Roughness= -0.76 , $R^2 = 0.97$.

Evidence exists that the Pacinian (FA2) receptors integrate vibrational signal power over time [156]. FA1's on the other hand, may play a role in vibratory sensation and may respond in a complex way to the frequency of the signal they receive. As stated in Section 1.2.2 the two receptors

have different frequency ranges at which they are most sensitive. If one of these two receptors is responsible for roughness perception with a probe, it should be possible to correlate its appropriately band-limited force signal power to subjective roughness perception. For example, the force signal can be partitioned into two bands of frequency: 5-50 Hz, the response range of the FA1 receptors, and > 50 Hz, the response range of the FA2 receptors. The power in the force signal is determined for each of these bands for each experimental trial. For each sinusoidal texture period this band-limited force signal power is averaged over subjects and iterations, using the same process used to average roughness estimates.

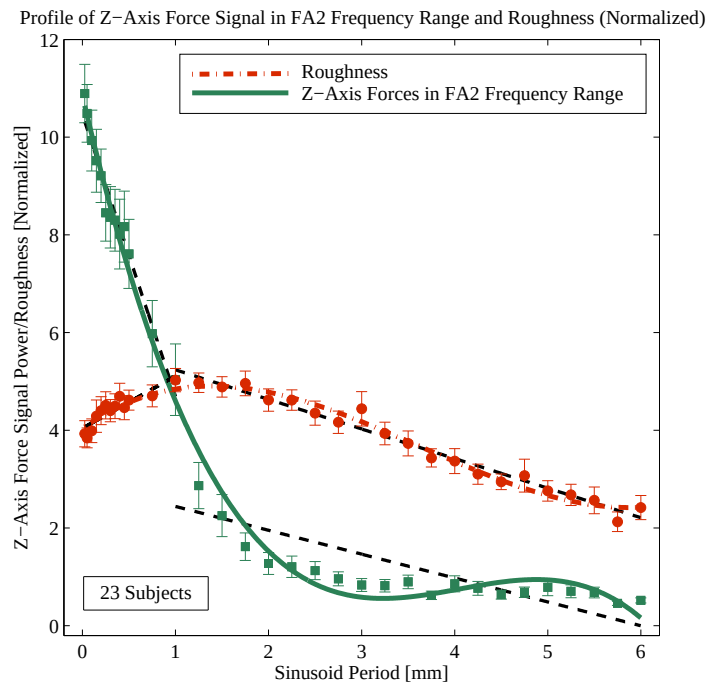


Figure 3.21: Power Spectral Density of z -axis forces within the FA2 receptor frequency range (50-500 Hz), compared to roughness as a function of sinusoid period. PSD and roughness are normalized for comparison. A third order fit to each data set is shown with a maximum at $0.025 \text{ mm}_{period}$ and $R^2 = 0.99$ for PSD and a maximum at 1.39 mm_{period} and $R^2 = 0.97$ for roughness. A 1-way ANOVA shows significant effects of sinusoid period on FA2 z -axis force signal power ($F(32,726)=77.6155$, $p= 0.00$). A linear fit to the initial ($< 1.0 \text{ mm texture period}$) and final ($> 1.0 \text{ mm texture period}$) portions of each curve with slopes as follows: Initial PSD= $-5.77 \text{ N/mm}_{period}$, $R^2 = 0.96$, Initial Roughness= 0.80 , $R^2 = 0.80$, Final PSD= $-0.49 \text{ N/mm}_{period}$, $R^2 = 0.52$, Final Roughness= -0.61 , $R^2 = 0.97$.

The band-limited force signal power function ($\Phi(I)$) for FA1 and FA2 receptors can be seen in Figures 3.20 and 3.21. In these figures the force signal power function is normalized to the psychophysical roughness function which is shown for comparison. It is clear that neither the FA1 or FA2 bandwidths correlate exactly with roughness (see Table 3.3) although the FA1 function demonstrates a similarly shaped curve, with a fairly close fit in descending slope over larger sinusoidal texture periods. The FA2 bandwidth has a steep initial negative slope where the roughness function has a corresponding positive slope. For textures greater than 1 mm in period, however, the final slopes of the roughness and the FA2 band-limited force signal are nearly identical. This may reflect a relationship between higher frequency power and the roughness of large period textures.

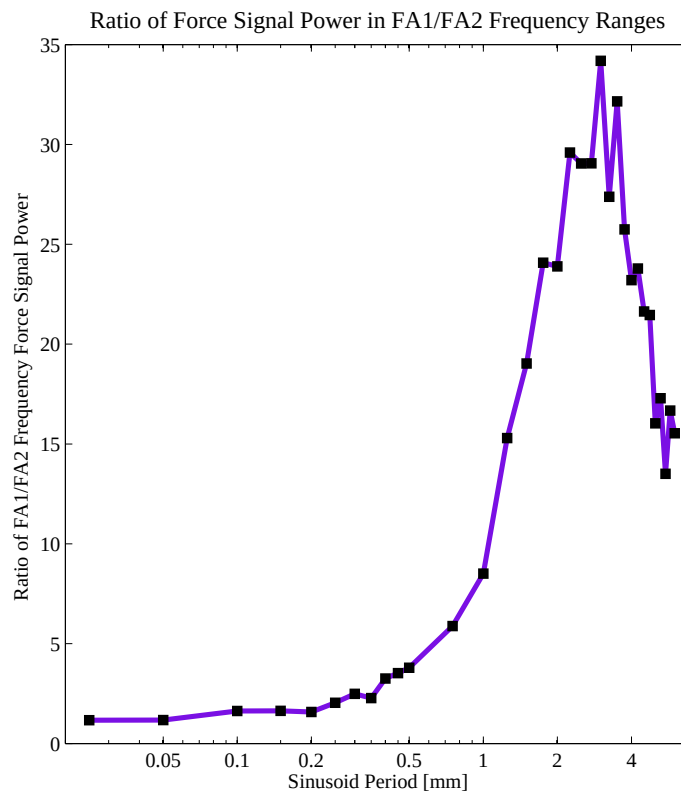


Figure 3.22: Power Spectral Density of z -axis forces within the FA1 receptor frequency range (5-50 Hz) divided by PSD for FA2 receptor frequency range (50-500 Hz) as a function of sinusoid period. This ratio indicates the relative power of the low frequency force signal to the high frequency force signal.

Since the total power in the force PSD spectrum is clearly related to roughness perception and most of the power in the spectrum is concentrated in the FA1 bandwidth for most texture periods (see Figure 3.22), it seems likely that the FA1 bandwidth is primarily responsible for roughness

perception. This is further supported by the evidence of Figure 3.23. This figure shows the cor-

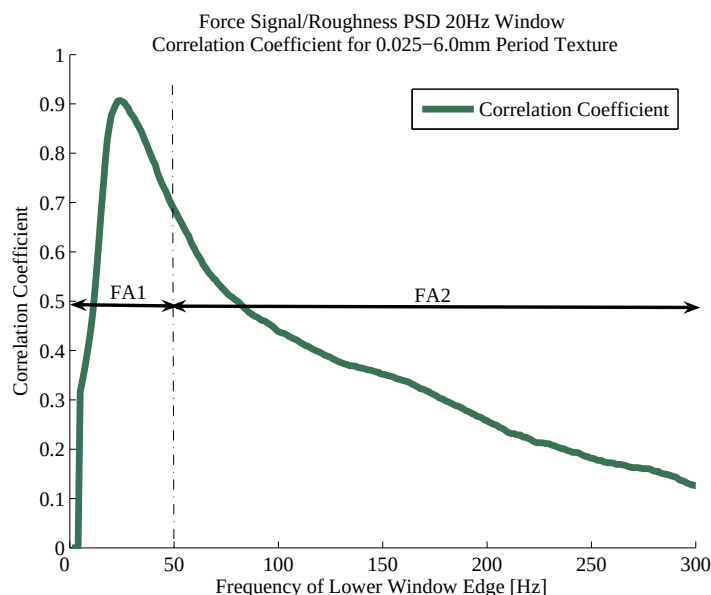


Figure 3.23: Correlation coefficient between subjective roughness and the power in the force signal in a 20 Hz window sliding across the PSD periodogram. The window’s lower edge is at the frequency displayed on the x axis. The FA1 and FA2 frequency bandwidths are indicated with arrows.

relation coefficients between the power in a 20 Hz frequency window of the force signal and the psychophysical roughness function. The window moves across the frequency range of 500 Hz from low to high. The approximate peak in correlation (0.90) occurs when the window is at 20-40 Hz which is well within the FA1’s sensitive bandwidth but outside the FA2’s.

Still, some questions are raised by this experiment’s finding that neither the FA1 or FA2 bandwidths correlate with roughness as well as their combined bandwidth. First, are both receptors active in roughness perception?

In Figure 3.24 a series of PSD frequency windows is correlated with roughness. The window’s initial value is always 5 Hz while the final value, displayed on the abscissa, is increased in 1 Hz increments. As the window increases in size, the integrated power from more and more frequencies is used to determine a force function ($\Phi(I)$) which can be correlated with the subjective roughness function ($\Psi(I)$). The figure demonstrates that, while the correlation coefficient rises to levels > 0.80 at approximately 100 Hz with a p -value < 0.01 , there is a continued slow but steady improvement in correlation with increasing window size. Most of the signal that results in roughness perception appears to be coming from frequencies below 50 Hz but higher frequencies, up to 350 Hz, appear

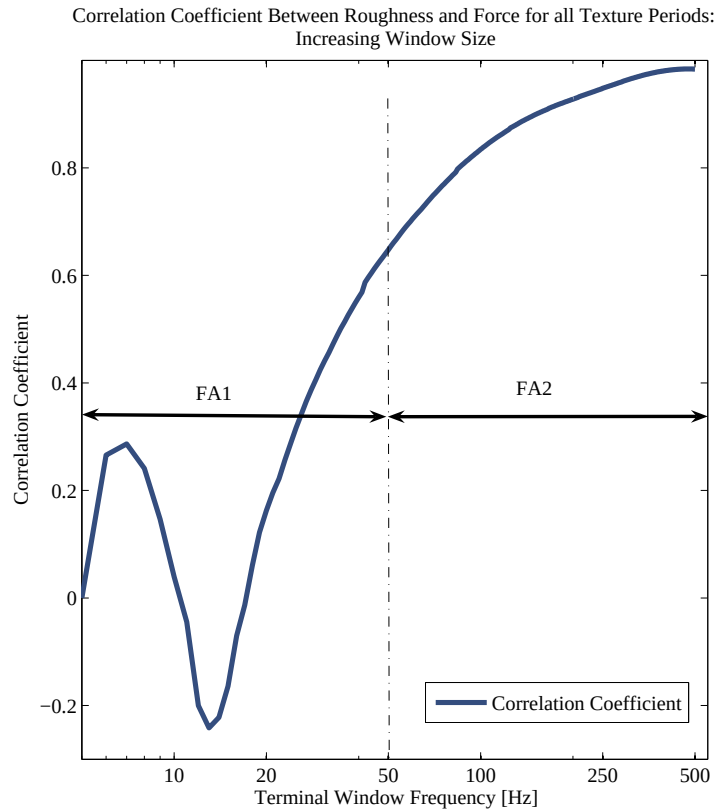


Figure 3.24: Correlation coefficient between subjective roughness and the power in the force signal in a frequency window of increasing size. The window's lower frequency is fixed at 5 Hz. The correlation coefficient is plotted against the the window's upper frequency which is used as the independent variable. The FA1 and FA2 frequency bandwidths are indicated with arrows.

to be required to achieve correlations of > 0.98 . This suggests that the FA1 receptors are primarily responsible for roughness perception but that FA2s also play a role, although a small one.

If the total power of the force signal characterizes the perception of roughness, it is possible that both low and high frequency receptors are important for indirect roughness perception with a probe. Is it possible that the FA1 and FA2 receptors play different rolls for textures with large and small periods? Previous studies have shown that, for direct texture, two receptors are implicated: SA1s for large textures and FA2s for small textures [53]. It seems logical to anticipate that small period textures will generate high frequency changes in force. Thus roughness for small periods should be more influenced by the power in the higher frequency bands of the force signal. The opposite should be true for large period textures which should have a perceived roughness that is sensitive to low frequency signals.

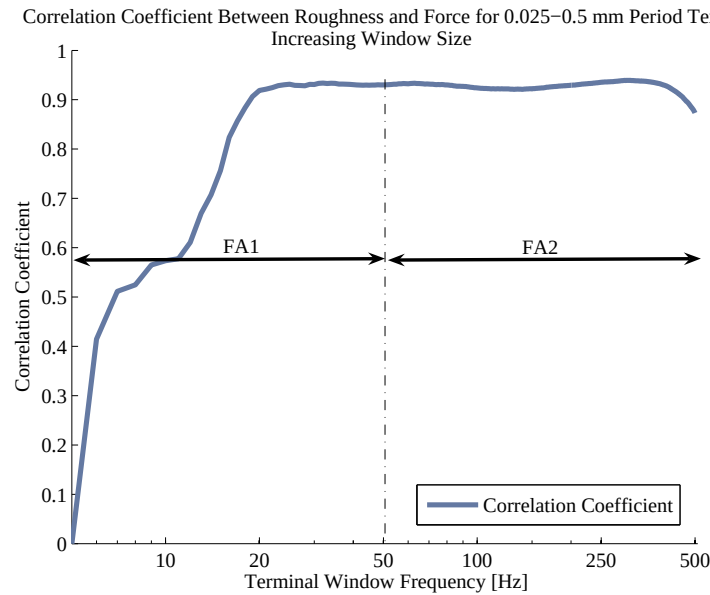


Figure 3.25: Correlation coefficient between subjective roughness and the power in the force signal for small period (0.025-0.5 mm) sinusoidal textures in a frequency window of increasing size. The window's lower frequency is fixed at 5 Hz. The correlation coefficient is plotted against the the window's upper frequency which is used as the independent variable. The p-value of the correlation coefficient is also shown.

To test this hypothesis, the power of the force signal is again examined with windows of increasing size. The roughness functions for small (0.025-0.5 mm) and large period textures (2.0-6.0 mm) are found separately. The definitions of small and large period textures derive from the observation that they span regions of the roughness function that are approximately linear. Figure 3.25 shows the results for small period textures while Figure 3.26 shows a similar result for large period textures. It is interesting to note, that large and small period textures are both highly correlated with roughness for frequency windows of less than 50 Hz. The correlation of large period texture rises more slowly, as window size increases, than does the small period texture.

It is not apparent why both large and small period textures are both highly correlated with the low frequency portion of the force signal while the entire range of sinusoidal texture periods requires both high and low frequency portions of the spectrum. The force signals at the extremes of the texture period range are linear functions while those in the mid-range display an inflection point, shifting from rising power to declining power with respect to texture period. Potentially, this inflection point captures subtle nuances of the relationship between perceived roughness and the force signal's power, in particular relying on higher frequencies of the force signal for improved correlations.

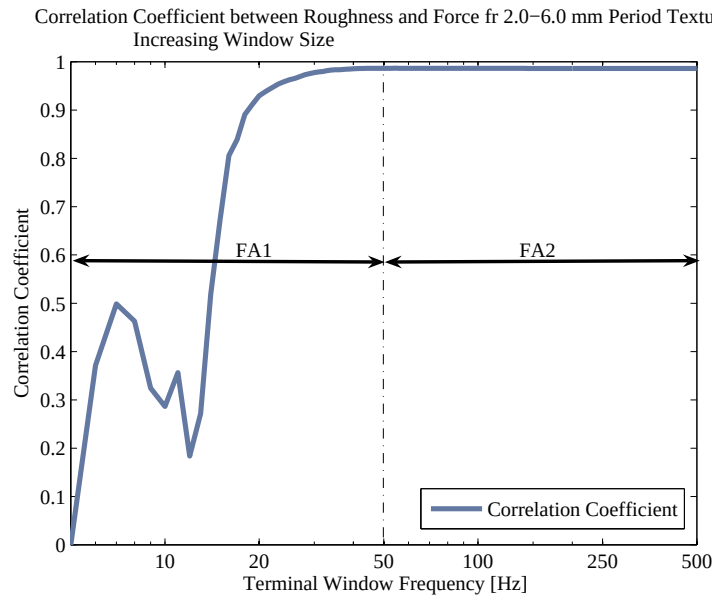


Figure 3.26: Correlation coefficient between subjective roughness and the power in the force signal for large period (2.0–6.0 mm) sinusoidal textures in a frequency window of increasing size. The window’s lower frequency is fixed at 5 Hz. The correlation coefficient is plotted against the the window’s upper frequency which is used as the independent variable. The p-value of the correlation coefficient is also shown.

Taking correlation coefficients between the psychophysical function for roughness and all of the physical properties investigated demonstrates that the total power in the force signal is capable of explaining more of the variance in the roughness psychophysical function than any other property (see Table 3.3). Multilinear regression and principal component analysis, using all of the investigated physical properties, further support this hypothesis.

Stepwise multilinear regression reveals that the variance in the psychophysical function for roughness is almost entirely accounted for by the total power in the force signal, with an R value of 0.984 with a significance of $p < 0.001$ ($df=1/31, F=926.7$). Statistical evaluation using principal component analysis suggests that there are two factors, almost evenly weighted, responsible for roughness perception. The identity of the two factors is not known, however, velocity, kinetic energy, maximum PSD power and PSD total power reflect high loadings of one component while acceleration, standard deviation of the z -axis force, and the power in the FA2 band-limited PSD for force show high loadings of the other.

Physics Parameter	Sum of Squares Difference	Correlation Coefficient	p-value
Mean Position	0.0415	0.12	> 0.05
Velocity	0.0418	0.50	< 0.005
Kinetic Energy	0.1287	0.03	> 0.05
Position Power	0.0832	-0.30	> 0.05
Acceleration	0.0297	0.78	< 0.001
Mean Force	0.0424	-0.18	> 0.05
Maximum Force in PSD	0.0765	0.23	> 0.05
Frequency of Maximum Force in PSD	0.0195	0.76	< 0.001
Force PSD FA1 Power	0.0578	0.65	< 0.001
Force PSD FA2 Power	0.7514	0.45	< 0.01
Force PSD Total Power	0.0046	0.98	< 0.001

Table 3.3: Correlation coefficients for various physics parameter functions when compared to the psychophysical roughness function for sinusoidal gratings with periods from 0.025-6.0 mm. Sum of Squares difference is the square of the difference between the parameter function and the roughness function divided by the square of the roughness function for normalization.

3.5 Conclusions

The investigation of roughness perception with sinusoidal gratings has demonstrated that the MLHD is capable of producing textures with relatively small periods. The attenuation of the output position signal for small periods and high frequencies serves as a *caveat* for the use of haptic devices for small scale textures whose elements will require high frequency outputs for accurate representation. The PHANTOMTM, which has a position bandwidth of approximately 50 Hz [19], would likely produce severely attenuated textures for any sinusoidal period less than 0.2 mm. Such attenuation would be highly dependent on subject hand velocity. For example, hand velocities of 50 mm/s, commonly seen in this thesis' experiments, would result in attenuation of sinusoidal texture for periods < 1 mm. This may explain the inter-subject variance of the psychophysical function found by some researchers using the PHANTOMTM [68]. It would also explain the reason that, for large scale textures but not small, the MLHD produces a power law exponent which is in good agreement with PHANTOMTM based studies.

The physical property which accounts for texture roughness appears to be force variability (force signal power). Significantly, the power in the lower frequency range correlates well with roughness although higher frequencies seem to play a role as well. This indicates that, while the FA1's are likely the most significant mechanoreceptor for roughness perception with a probe, the FA2's may also play a subsidiary role.

Chapter 4

Probe Size Effects with Trapezoidal Grating Textures

4.1 Introduction

A primary motivation for studying conical texture gratings is to investigate how the relationship between the geometry of the probe and the texture affects human roughness perception. Does the shape and size of the probe, and the topology of the texture change the way in which roughness is experienced?

Previous psychophysical studies [64, 68, 107, 148] have investigated roughness perception using virtual haptic textures made up of sinusoidal gratings such as those examined in Chapter 3. These studies rendered the haptic interaction point (HIP) as an infinitely small point, sometimes called a zero-width virtual haptic probe or point-probe. Investigating sinusoidal textures with a point-probe is simple and greatly reduces the complexity required to generate haptic textures, however, it oversimplifies probe-surface geometry, ignoring important effects that this relationship may have on roughness perception. Previous investigations [66, 136, 141] have demonstrated that probe and texture geometry affect the form of the roughness perception function for both real and virtual textures.

The results of sinusoidal virtual texture experiments prior to this thesis have diverged substantially from studies that used dithered conical elements and spherical probes, especially with regard to the form taken by the roughness perception psychophysical function. These virtual textures have been found to have linear psychophysical functions with either positive or negative slopes [64, 68, 107, 148]. On the other hand, real spherical probes used on dithered conical element textures have generally been found to produce inverted "U"-shaped psychophysical functions [66, 77].

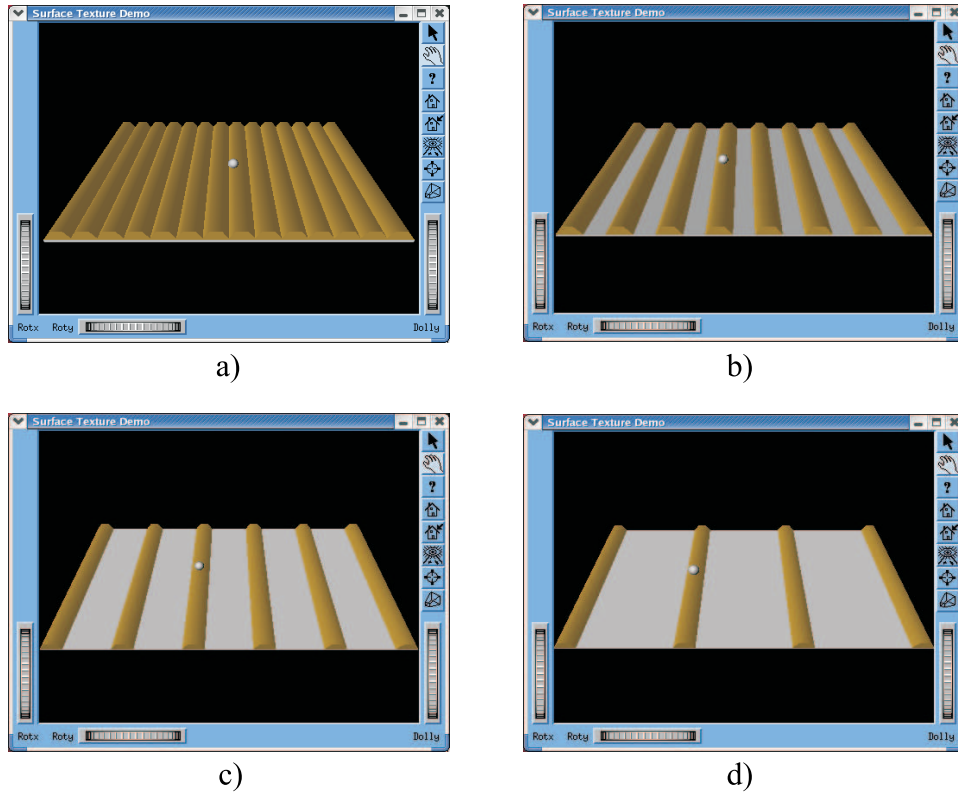


Figure 4.1: Graphic representation of four examples of trapezoidal grating texture used for psychophysical experiments with a (a). 0.96 mm period, (b) 1.96 mm period, (c) 3.46 mm grating and (d) 5.96 mm grating..

These roughness functions have been described in terms of a model, based on the geometric relationship between the probe and texture, which predicts the location of maximum roughness with respect to element spacing [66].

The trapezoidal grating experiment was designed to determine if adding size and shape to the virtual probe would affect the way in which texture was perceived. It was hypothesized that a spherical probe, interacting with a regular set of elements would produce a psychophysical roughness perception function different from that seen with a point-probe interacting with a sinusoidal texture.

4.2 Spherical Probe and Trapezoidal Grating Constraint Surface Algorithm

The motivation for choosing trapezoidal grating elements is twofold. First, the element shape is similar to the conical elements used by Klatzky *et al.* in their studies on the effect of probe geometry on real texture perception [66]. Second, there is some evidence that while real grating textures and

probes produce non-linear psychophysical functions for roughness, these grating functions also differ from the inverted "U"-shaped curves found for dithered cones [74]. The trapezoidal grating is a compromise between dithered elements and sinusoidal texture. Ideally, it should generate a roughness function different from sinusoids and with significant differences between probe sizes.

The shape of the grating elements used in the trapezoidal grating experiment was dictated by several constraints. First, to allow for direct comparisons, the elements needed to be similar to previously investigated sinusoidal textures: periodic and stretching completely across the texture surface along the y axis in the form of a grating. The experimental results were also intended for comparison with Klatzky's study of dithered conical elements. The overall trapezoidal shape of the elements was therefore chosen to be comparable to her study's real ones [66]. This requirement dictated that the height, el_h , of the elements be 0.42 mm with a plateau width or land, el_{pw} , of 0.46 mm and a base width, el_{bw} , of 1.04 mm. These dimensions result in an element side angle, α , of 53° (see Figure 4.2).

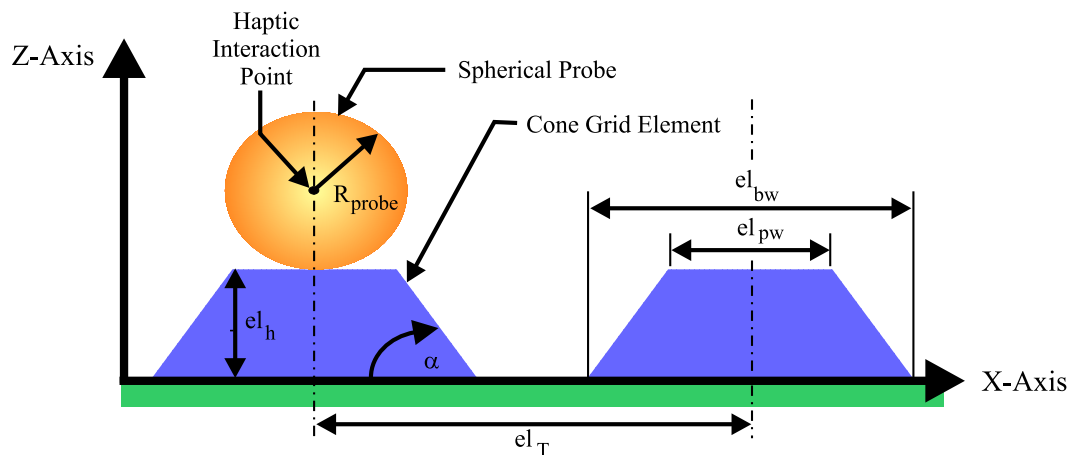


Figure 4.2: Cross-section of trapezoidal grating texture with dimensions.

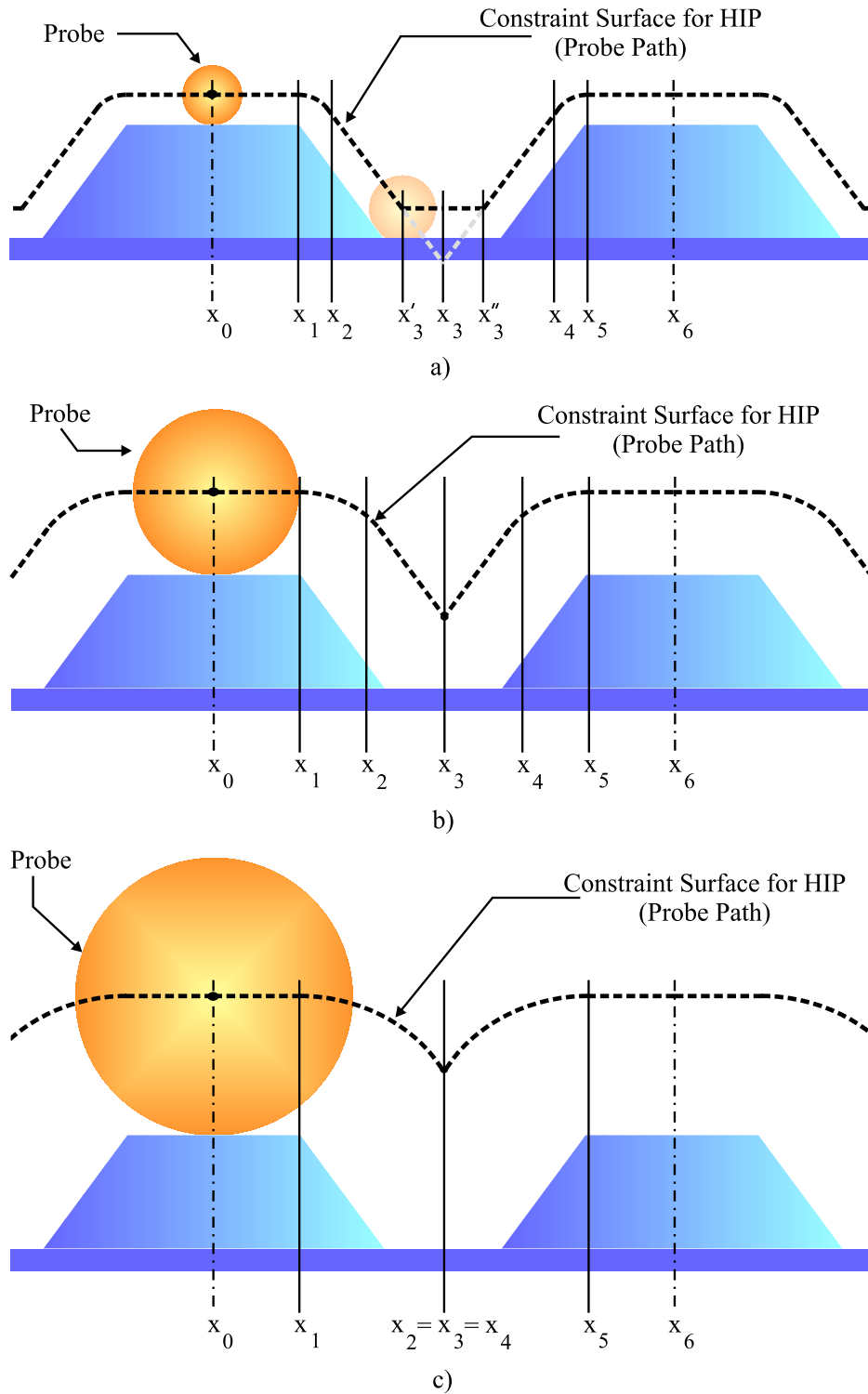


Figure 4.3: Cross-section of trapezoidal grating texture with inflection points. a) Small probe. b) Larger Probe. c) Very Large Probe.

Element period, el_T , is considered to be the separation of the centers of the lands of adjacent elements. Eleven element periods ranging from 0.5-5.5 mm were initially selected for use in the trapezoidal grating experiment. This range was chosen to cover the periods most commonly seen in the psychophysical literature for real and virtual textures.

The larger end of the range of periods (5.5 mm) is also dictated by the limited workspace of the maglev haptic device (± 12 mm). When el_T is 5.5 mm, at most 4 grating elements can be encountered as subjects traverse the workspace; fewer elements than this may be interpreted as a complete lack of texture surface features by subjects who fail to use the full workspace during texture exploration.

The smaller end of the range, 0.5 mm, should produce a temporal frequency of 100 Hz when a subject moves the manipulandum at 50 mm/sec, the typical mean velocity determined in previous experiments. This is within the 120 Hz position bandwidth capability of the MLHD.

Unfortunately, due to a programming error in setting up the experiment, the distance between x_1 and x_5 , as seen in Figure 4.3 (the distance between the adjacent lips of two elements) was mistaken for el_T . This introduced an unintended systematic bias of +0.46 mm into the texture period, making el_T 's actual range 0.96-5.96 mm. While this biased range of periods is larger than initially planned, it still captures most of the originally intended range and contains the drop points predicted by the geometric model of roughness perception for the probe sizes used in this experiment (see Section 4.4 and below).

A final consideration in the choice of element shape and spacing is symmetry. By using equally-spaced symmetric elements, the same set of parametric equations can be used for each period of texture. Additionally, symmetry allows the calculation of the HIP's desired height above the texture using only the location of the center of each texture element. If elements were allowed to be asymmetrical, the desired height might depend on more than one contact point between probe and elements, increasing the complexity of the virtual texture algorithm substantially.

A spherical probe shape is chosen for similar reasons. First, it is important to select probe sizes and shapes similar to those used in previous real texture experiments to allow for comparisons. Klatzky *et al.* used real spherical probes to study indirect touch [66]. For this thesis, the most important of Klatzky *et al.*'s findings were those that dealt with texture perception with a stylus and used spherical styluses with radii from 0.5-1.5 mm. The probe radii, r_{probe} 's, in the trapezoidal grating experiment are 0.25, 0.5, 1.0 and 1.5 mm. These radii, taken together with the size, shape and spacing of the grating elements should, according to the geometric model, produce maximum

roughness at element periods of 1.31-2.56 mm (see Table 4.1). These periods are within the selected range of element spacings. The spherical shape of the probe provides symmetry which, as in the case of symmetrical texture elements, simplifies the constraint surface algorithm (CSA) substantially.

With reference to Figures 4.2 and 4.3 the CSA works in the following way. First, the positions of the centers of a set of grating elements are defined with respect to the haptic workspace. The elements are equally spaced with a period, el_T . A set of parametric equations, operating on the x -axis location of the HIP, cover el_T and describe the HIP's desired z -axis position. The end-points of the parametric equations are a set of pre-calculated inflection points. Inflection points are determined by probe size and underlying texture geometry. The overall function defined by the equations is C_1 continuous except at the inflection point x_3 (see Figure 4.3).

The inflection points for a single period of texture can be seen in Figure 4.3. The size of the probe relative to element spacing defines three conditions which alter the shape of the constraint surface that the HIP follows. In the first condition (Figure 4.3a), the probe is small with respect to el_T and can fall between and slide along the bottom of the valley between elements. The second condition (Figure 4.3b), occurs when the probe size is too large to contact the floor of the valley but is still small enough to move parallel to the sloping side wall of an element before reaching the midpoint (x_3) of the inter-elemental valley. The last condition (Figure 4.3c), occurs when the probe is much larger than el_T and is still sliding over the lip of an element when it's center reaches x_3 .

For all of these conditions, the inflection point at the center of an element's plateau is designated x_0 . The current position of the HIP is x . If the subject starts to move the probe along the x axis, x_1 will be the down-going lip of this element and the z -axis desired position, z_{des01} , of the HIP in the interval (x_0, x_1) will be the combination of the element height, el_h and the probe radius, r_{probe} .

$$x_0 \leq x < x_1 : z_{des01} = el_h + r_{probe}, \quad (4.1)$$

If a spherical probe with radius r_{probe} travels around a convex corner that has greater curvature than the probe itself, it moves along an arc with radius r_{probe} . Otherwise, it moves a distance r_{probe} from the surface and parallel to it. This property has previously been used to reconstruct surfaces during robotic exploration with spherical fingers [101, 102]. Since the lip of a trapezoidal element has infinite curvature, the motion of the HIP around it will be along an arc with the same radius as the probe. This arcing motion will persist from x_1 to x_2 and is defined as

$$x_1 \leq x < x_2 : z_{des12} = el_h + \sqrt{r_{probe}^2 - (x - x_1)^2}, \quad (4.2)$$

x_2 is the point at which the tangent to the HIP's arc of motion is equal to the slope, α , of the side of the element wall.

From x_2 to x_3 a small enough probe (Figure 4.3a and 4.3b) will travel parallel to the element side wall:

$$x_2 \leq x < x_3 : z_{des23} = \tan(\alpha)(x_2 - x) + z_{des12}, \quad (4.3)$$

If, however, the HIP reaches x_3 before this tangency condition is met, x_2 , x_3 , and x_4 are functionally equivalent and the HIP will never move in parallel to the element wall. This occurs with the large probe in Figure 4.3c.

For the smallest probe (Fig. 4.3a) the HIP reaches a height equivalent to r_{probe} above the texture base, before it reaches x_3 , it is forced to stay at that height (r_{probe}) as it moves along the x axis starting at x'_3

$$x'_3 \leq x < x''_3 : z_{des3'3''} = r_{probe}, \quad (4.4)$$

until it contacts the base of the next element at x''_3 . At x''_3 it begins to move parallel to the next element's sloping wall until it reaches x_4 where the angle of the wall and the tangent to the radius of the spherical probe are equal. For the smallest probes (Fig. 4.3a)

$$x''_3 \leq x < x_4 : z_{des34} = \tan(\alpha)(x - x''_3) + z_{des3''}, \quad (4.5)$$

while for the larger probes of Figure 4.3b using

$$x_3 \leq x < x_4 : z_{des34} = \tan(\alpha)(x - x_3) + z_{des3}. \quad (4.6)$$

From x_4 to x_5 the center of the probe moves along an arc that has a curvature equivalent to a sphere with radius r_{probe} until the up-going lip of the new element is reached at x_5 .

$$x_4 \leq x < x_5 : z_{des45} = el_h + \sqrt{r_{probe}^2 - (x - x_5)^2}, \quad (4.7)$$

From x_5 to the element center, x_6 , the HIP will follow a course parallel the top of the cone but r_{probe} distance above it

$$x_5 \leq x < x_6 : z_{des56} = el_h + r_{probe}. \quad (4.8)$$

The point x_6 on the x axis ends one period (el_T) of texture and begins the next (x_0). Identical parametric equations are used for each period and the number of periods the HIP traverses is determined by the width of the workspace and the distance a subject moves the manipulandum. The workspace is artificially limited to ± 10 mm to prevent accidental hard contacts between flotor and stator. This limit means that, for the range of el_T selected, the number of elements ranges from 4 to 20 (see Figure 4.1).

4.3 Trapezoidal Grating Experimental Design

The experimental setup for the trapezoidal grating experiments was effectively the same as that of the sinusoidal texture experiment described in Section 3.2. The primary difference between the two experiments was that 4 spherical probes of varying radius were used in the trapezoidal experiments instead of the single point-probe used in the sinusoidal grating experiments.

As in the sinusoidal texture experiment described in Section 3.2, subjects were seated approximately 50 cm from a computer monitor with their right hand on the haptic device manipulandum. Subjects were allowed up to one hour to complete the trials but most finished within 20 minutes. Subjects could not see the texture and wore headphones playing white noise to prevent auditory identification of texture properties.

Subjects were asked to assign a numeric value to the roughness of the texture which they were exploring. They were not allowed to use numbers less than or equal to zero and were informed that large numbers should correspond to surfaces that were rougher and small numbers to surfaces that were less rough. No scale was given or suggested.

The experiment was divided into four blocks; one block for each probe size. The order of the blocks was randomized between subjects to prevent learning effects. Nine female and 17 male subjects for a total of 26 subjects, including 3 left-handed subjects, performed the experiment. Left-handed subjects used their non-dominant hand to perform the experiment. Subjects were all drawn from the student population at Carnegie Mellon University and most were from the psychology undergraduate student pool. They received credit towards their degree program for participation in psychological studies such as this. The remainder were graduate student volunteers from the Carnegie Mellon Robotics Institute.

An experimental trial consisted of a subject exploring a single texture period with a single probe radius. Three iterations of each probe-size/texture-period combination were performed by each subject. Four probes sizes, eleven texture periods and 3 iterations produced 132 trials per subject.

Each of the four experimental blocks began with a set of demonstration trials during which the subject explored six texture periods with the probe size used in the upcoming block. The six texture periods were representative of the range of periods about to be presented in the upcoming block and included its extremes. They were presented in random order.

Each demo was followed by a block of 33 experiment trials in which subjects entered a numeric value for the subjective roughness they experienced during the trial. Each trial represented a pairing of probe size and texture spacing. Probe size was constant within the block, while the ordering of spacings was randomized. This arrangement precluded direct comparison of roughness magnitude levels between blocks since subjects could utilize different magnitude estimation scales for each block. Manipulandum position and forces commanded by the MLHD were recorded during the entire experiment at 1000 Hz.

4.4 Trapezoidal Gratings and Roughness Perception

Individual subject's psychophysical functions ($S_i = \Psi(I_i)$) can be seen in Figure 4.4 along with second order fits to each subject's normalized data. It can be seen that roughness estimates follow a pattern which is relatively invariant between subjects. An average of the curves is superimposed on individual functions. While a second order fit may not be ideal for these data, its average R^2 value across subjects and probe types is 0.85, substantially better than the averaged linear fit R^2 of 0.69. This indicates that individual subjects do not perceive texture as a linear function of element spacing for trapezoidal grating texture and the trends seen in cross-subject aggregate data are valid.

The psychophysical function, $S = \Psi(I)$, for roughness perception was obtained by combining the subject data for each probe size using the averaging and normalization techniques described in Section 2.3.2. Figures 4.5 and 4.6 show log-log plots of $\Psi(I)$. The aggregate psychophysical function data is well-fitted with either a second order quadratic or third order polynomial as can be seen in Table A.1. R^2 values for a second order fit range from 0.93-0.98 while those for a third order fit are slightly better.

Examining the location of the maxima of the psychophysical functions seen in Figures 4.5 and 4.6, it can be observed that, for both second and third order fits, the maxima move to larger

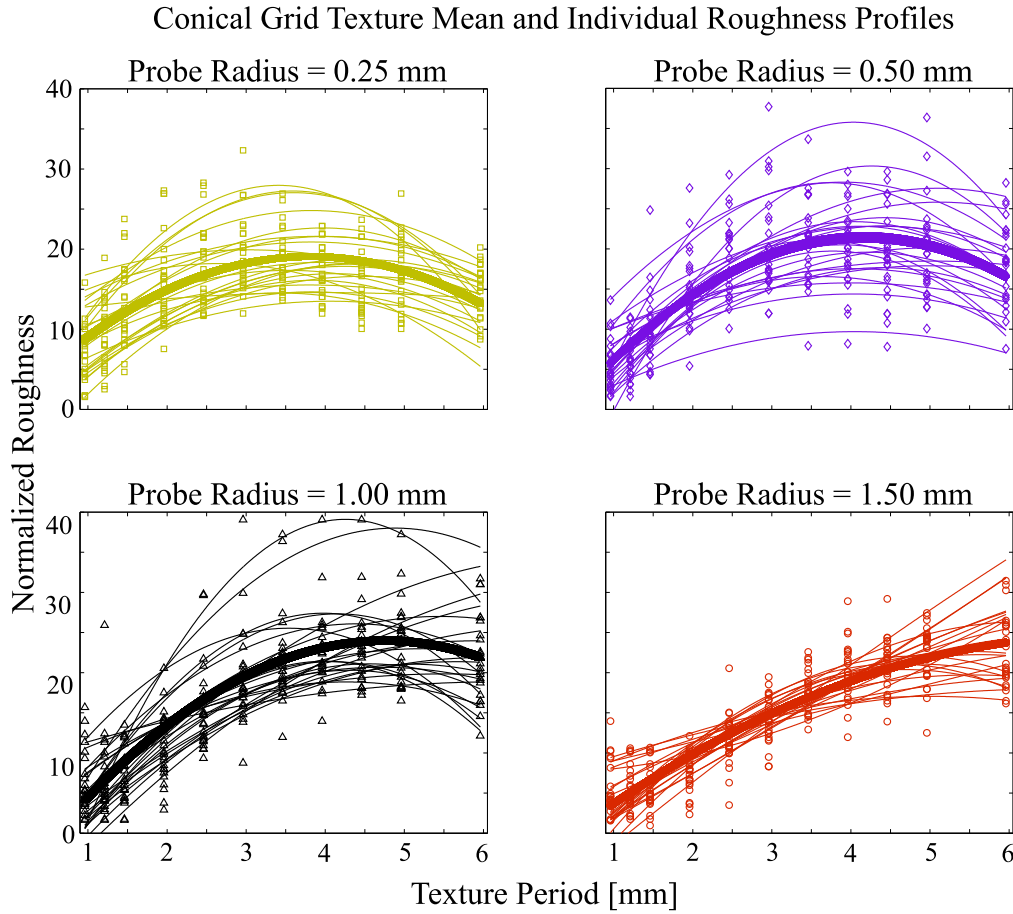


Figure 4.4: Trapezoidal grating roughness functions for 4 different probe sizes. Individual subject functions are shown as thin lines while the mean function for each probe size is shown as a thick line.

texture periods as probe size increases. This behavior is not unexpected since a geometric model of probe and texture interaction, developed for real textures and probes by Klatzky *et al.*, provides an explanation for the phenomenon [66].

With the geometric model, a subject's roughness perception is considered to be based on the distance to which the probe penetrates between two elements: the deeper the penetration, the greater the magnitude of perceived roughness. When elements are closely spaced, a spherical probe is unable to penetrate fully between them. When the spacing is large enough the spherical probe drops completely to the floor between elements, at the so-called drop point (DP), and maximum roughness perception occurs.

Taking the simplest case, if a spherical probe rests between two rectangular grating elements the DP may be found based on the texture period, el_T , the grating width el_{pw} , and the radius of the probe, r_{probe} (see Fig. 4.7a). The elements are separated by a gap, el_{sep} , of

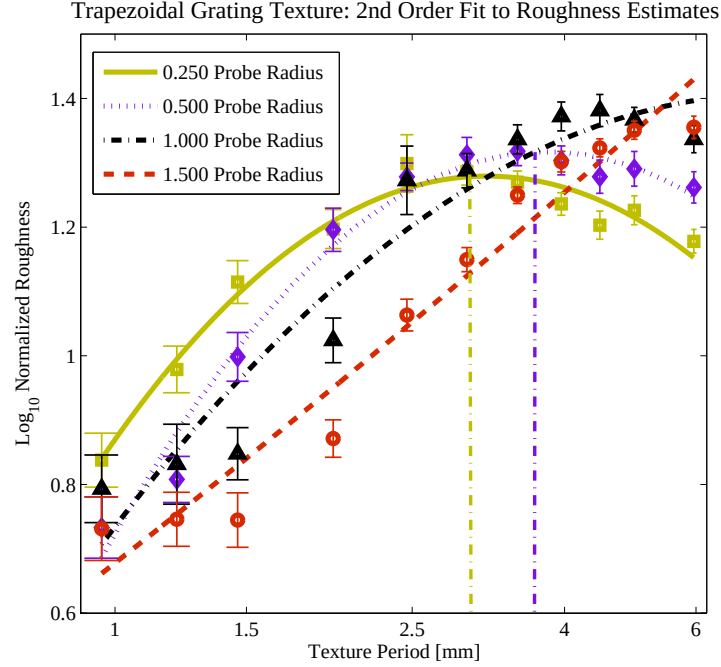


Figure 4.5: Semilog plot of second order fit to mean log normalized roughness estimates of trapezoidal grating textures with various spacings explored with spherical probes of 0.25, 0.5, 1.0 and 1.5 mm radius. Vertical lines indicate maxima (Drop Points).

$$el_{sep} = el_T - el_{pw}, \quad (4.9)$$

When $el_{sep} = r_{probe}$, the probe can drop fully thus the drop point is

$$DP = r_{probe} + el_{pw}. \quad (4.10)$$

The depth of penetration at any texture period can be determined from

$$p_d = r_{probe} - \sqrt{r_{probe}^2 - (el_{sep}/2)^2}. \quad (4.11)$$

The geometric model for trapezoidal elements is only slightly more complicated. In this case, the penetration depth, p_d , of the sphere will be defined by texture element separation, el_{sep} , element side angle, α , plateau width, el_{pw} , and the radius of the probe (as defined in Fig. 4.7b).

$$p_d = (el_{sep}/2) \tan \alpha - r_{probe}(\sin \alpha \tan \alpha + \cos \alpha - 1). \quad (4.12)$$

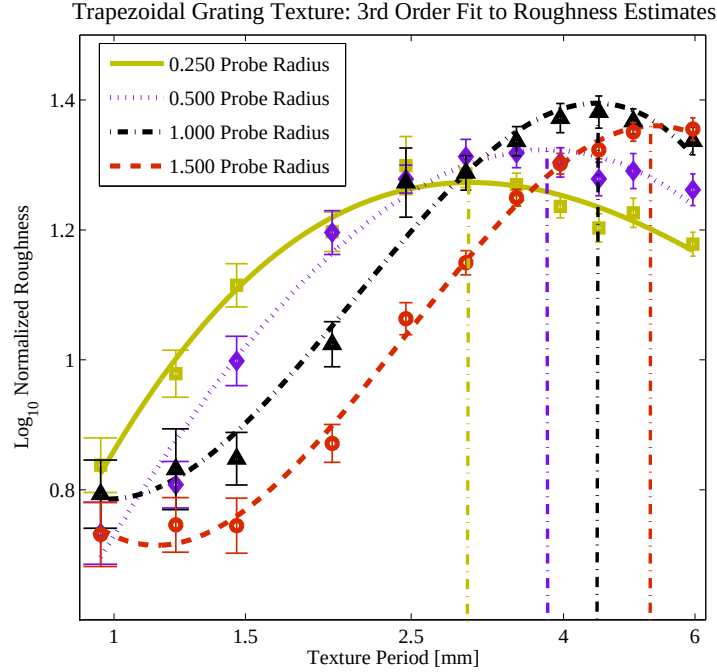


Figure 4.6: Semilog plot of third order fit to mean log normalized roughness estimates of trapezoidal grating textures with various spacings explored with spherical probes of 0.25, 0.5, 1.0 and 1.5 mm radius. Vertical lines indicate maxima (Drop Points).

The drop point will occur when the penetration depth is equivalent to the height of the elements el_h :

$$DP = el_{pw} + \frac{2(el_h + r_{probe}(\sin \alpha \tan \alpha + \cos \alpha - 1))}{\tan \alpha}. \quad (4.13)$$

Equation 4.13 predicts that as probe size increases the DP will occur at larger and larger spacings. Intuitively, this is because larger probes require larger element spacings before they can fully penetrate between grating elements. The location of the maxima of the experimentally determined psychophysical functions for four different probe sizes, as well as those the geometric model predicts for the same probe sizes, can be seen in Table 4.1. It should be noted that the location of the maxima of the fitted function with respect to element spacing represents an approximation of the DP. The DP itself is calculated from the geometry of the probe-texture interaction.

Table 4.1 shows that, regardless of the kind of fit chosen for the roughness function data, the DP increases with element spacing. At the same time, it reveals that both second and third order fits tend to produce maxima which are underestimated by the geometric model. It is also important

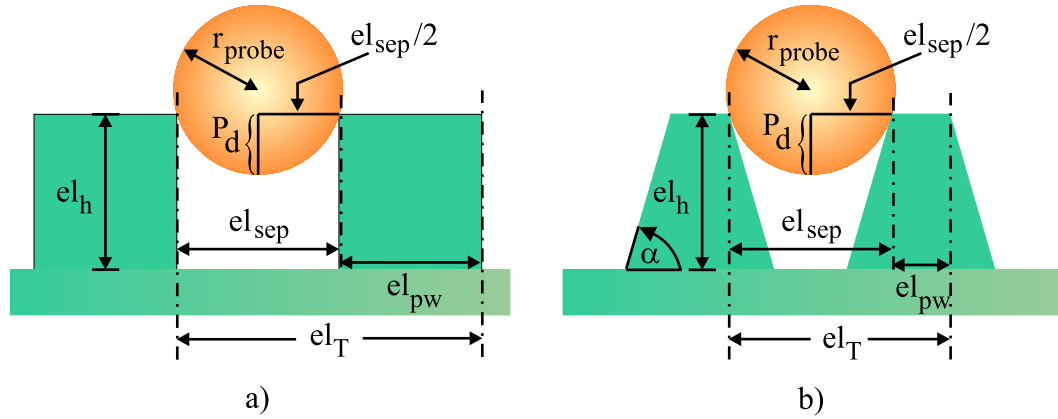


Figure 4.7: a) Penetration depth, P_d , is calculated from the radius of the probe, r_{probe} , and the separation of the elements, el_{sep} for rectangular texture elements. The drop point in this case occurs when $el_{sep} > r_{probe}$. b) P_d is calculated from the r_{probe} , el_{sep} and element side angle α for conical or trapezoidal texture elements. The drop point is the point at which P_d is equal to element height, el_h .

Rad.	2nd Ord. Curv.	Pred. Max [mm]	2nd Ord. Max [mm]	3rd Ord. Max [mm]	Logis. Max [mm]
0.25 mm	-1.65	1.31	3.15	3.00	1.58
0.50 mm	-1.77	1.56	3.79	3.79	1.84
1.0 mm	-0.85	2.06	7.75	4.43	2.47
1.5 mm	0.077	2.56	N/A	5.30	3.39

Table 4.1: The trapezoidal texture period at which maximum roughness occurs based on 2nd and 3rd order polynomial curves fitted to roughness estimates averaged across subjects as well as the height of a fitted logistic curve (80% of max-min). Curvature of the 2nd order fitted curve (on a log-log plot) and the period of maximum roughness predicted by the geometric model are also shown. Results are shown for four probe sizes.

to note that a 1-way ANOVA for the effects of probe size on DP showed significance only for a third order fit and not a second (Table 4.2). These discrepancies may, in part, be due to the fact that the actual data do not really appear to be fit by either a second or third order function. Instead, a sigmoidal logistic curve seems a more likely fit.

Figure 4.8 shows an unconstrained nonlinear optimization fit of a logistic curve of the form:

$$y = C + \frac{A}{1 + e^{-\lambda(x-B)}} \quad (4.14)$$

Factor	DOF	F	p-value
Curvature	3/92	23.47	< 0.0001
2nd Order Maxima	3/92	0.52	> 0.05
3rd Order Maxima	3/92	34.26	< 0.0001

Table 4.2: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to subject roughness estimates.

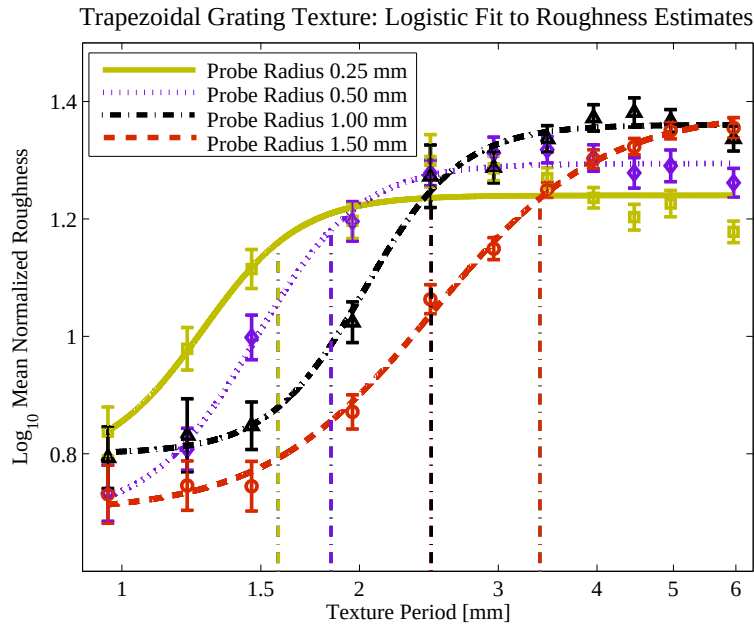


Figure 4.8: Unconstrained nonlinear optimization fit of logistic curve to roughness magnitude estimation data. Vertical lines indicate 80% of height of each curve. Sum of squared errors are 0.013, 0.004, 0.004, and 0.002 for each fit curve respectively. The fitted logistic curve was of the form $y = C + \frac{A}{1 + e^{-\lambda(x-B)}}$. Values of A , B , C , and λ may be found in appendix A

to the averaged and normalized roughness perception data. The sum of square errors is very low (see Appendix A) and the function appears to be well-suited to fit the data. The point at which the logistic curve nears its maximum could be considered the point of maximum roughness or the equivalent of the drop point. Arbitrarily choosing 80% of a logistic curve's y -axis range as a measure of the drop point, it can be seen that for a logistic fit, the drop point also increases with element spacing (Table 4.3). The DP's from the logistic curve are still generally larger than the predicted values.

The reasons for the underestimation of both the real and simulated drop point by the geometric model are unclear. It may be due to the model's underlying quasi-static assumption. The model

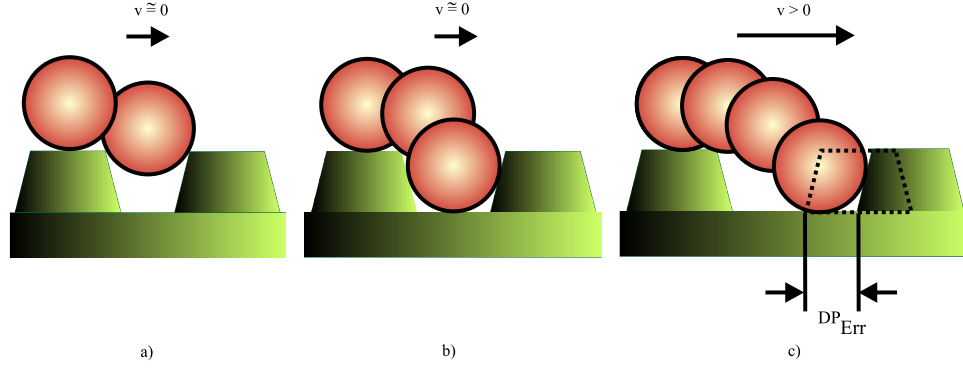


Figure 4.9: Drop point (DP) error explained by probe velocity and geometric model. In a) and b) when velocity is 0, DP is determined only by geometry. In c) with velocity greater than 0, DP is determined by probe velocity and geometry.

assumes that the depth of penetration is only related to the position of the probe with respect to texture geometry. Dynamic effects are ignored (Figs. 4.9a and b). The probe, in actual fact, has some velocity which will carry it forward as it falls to the floor between elements. Element separation must therefore be slightly larger than that predicted by the static model in order for a moving probe to reach the floor without contacting the next element's leading edge as seen in Fig. 4.9c. A subject's hand and the manipulandum are subject to the force of gravity, F , where

$$F = (M_{hand} + M_{manip})g. \quad (4.15)$$

M_{hand} and M_{manip} are the mass of the hand and manipulandum respectively and g is the acceleration due to gravity. This gravitational force governs the rate at which the probe falls. Thus an approximate idea of the increase in spacing, over and above what the geometric model predicts for the DP, can be calculated from element height, el_h , and the planar velocity, v_{xy} , of the probe. The difference between the velocity-based and quasi-static model predictions for the location of the drop point is termed DP_{err} and is determined as

$$DP_{err} = v_{xy} \sqrt{\frac{2el_h}{g}}. \quad (4.16)$$

Mean planar velocity (MPV) over all subjects, trials and probe sizes was determined from position recordings made directly from the MLHD during the experiment. Planar velocity in the trapezoidal experiments was found to vary little between probe sizes and was consistent with velocities used in real texture studies [12, 66, 81]. The mean x , y , and z -axis probe velocities at various

element spacings can be seen in Fig. 4.10. Using equation 4.16 and the measured MPV value of 51.08 ± 0.29 mm/sec a DP_{err} of 0.47 mm was found. This value approaches the average measured DP_{err} of 0.45 mm for the logistic fit to simulated trapezoidal texture and is close to the 0.24 mm average DP_{err} found with real dithered textures [66]. In previous studies, probe velocity has been found to affect the location of the DP, causing it to increase [66, 77]. This is consistent with the predictions of the revised geometric model since higher velocity will result in a larger DP_{err} .

The geometric model together with a velocity modification predicts the element spacing at which maximum roughness occurs for trapezoidal grating textures. It does not, however, explain why the inverted “U”-shaped psychophysical function seen with real dithered textures is not present with trapezoidal gratings. Rather, the trapezoidal gratings appear to become rougher as element spacing increases, reaching a steady plateau of roughness intensity. This plateau does not decline significantly even with further increases in element spacing (see Figure 4.8). The onset of this plateau is approximately predicted by the geometric model. This plateau also differs from the steady decline in roughness seen when sinusoidal gratings are experienced with a point-probe (see Section 3.3, Figure 3.3).

Although the cause of differences between dithered conical, and trapezoidal grating textures is unclear, it seems likely that element shape and layout play some role. Since the gratings were selected to have the same height, base and plateau widths, and side angles as Klatzky *et al.*'s cone elements, the major difference between the two textures is the regular spacing of the grating trapezoidal elements as opposed to their pseudo-randomly distributed cones.

Dithered cones allow a subject to pass around them when they are widely spaced, sliding off their sides. Thus, when cone spacing becomes wide enough, subjects will begin to move between the elements, passing over their shoulders, rather than traversing their full height. The vertical position change and encountered forces will be less than those expected if the probe were traversing the full height of the cone.

Gratings force a subject to cross over the full height of the element in order to move along the texture surface regardless of spacing. The probe cannot weave around the elements even if the spacing increases well beyond the point at which maximum roughness was first encountered. The vertical position change and encountered forces will therefore remain the same, regardless of spacing, once the DP has been reached.

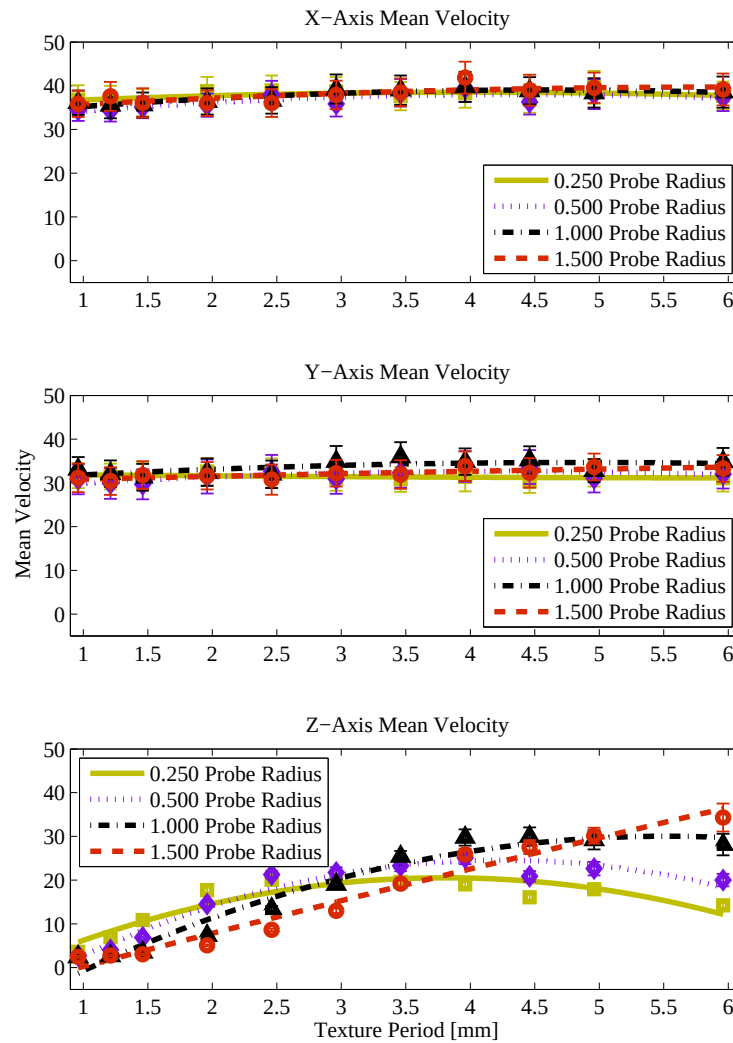


Figure 4.10: Plot of the mean velocity versus texture period for 3 axes. Texture period and probe size show no significant effect on x - and y -axis velocity. Z -axis velocity is significantly affected by both period and probe size.

The reason sinusoidal gratings differ from trapezoids in their psychophysical function is related to the type of probe used in each experiment. A point-probe is able to fully traverse the sinusoidal grating, passing through the full amplitude of the sinusoid, regardless of spacing. Thus, for sinusoid periods which the MLHD is capable of rendering without attenuation (see Section 3.3 for a discussion of attenuated sinusoids due to position bandwidth limitations), the vertical motion of the probe is identical. The slope of the sinusoid decreases with increasing period and thus the rate of change of position and force decrease. Thus, if the rate of change of position or force are the salient physical properties of roughness perception, then, with a sinusoid and a point-probe, the roughness should start near a maximum and decrease as sinusoid period increases. A small spherical probe will not show the same behavior with trapezoidal gratings since the side angle of the trapezoids is constant. Therefore, regardless of period, the rate of change of position or force will be the same as an element is crossed. The average over time, however, may diminish since elements are encountered less frequently. Thus, if the average change in position or force is responsible for perceived roughness, some sort of decline from peak roughness might also be expected with increasing period. The size of the decline would depend on the amount of time or space used by the perceptual system to integrate the signals.

4.5 Trapezoidal Gratings and the Physics of Roughness Perception

It is clear that the perception of roughness is different for sinusoidal gratings explored with point-probes and trapezoidal gratings explored with spherical probes. With sinusoidal gratings, roughness is initially high and then declines steadily with increasing period. With trapezoidal gratings it starts low and then increases steadily to a plateau. This thesis hypothesizes (see Section 1.3) that the physical property which is perceived as roughness should change with respect to element spacing in the same way that roughness itself does. Thus, differences in perceived roughness observed between sinusoidal and trapezoidal textures should be matched by similar changes in measurements of the physical properties themselves. The property associated with roughness should correlate with roughness perception for both sinusoidal and trapezoidal textures.

Since changes in the size of the probe induce changes in the psychophysical function for roughness, noticeable differences should also exist in position and force measurements made during subjects' evaluation of the texture. In figure 4.11, a representative sample of the x , y , and z -axis position over time with four different probe sizes can be seen. These samples use a texture with a

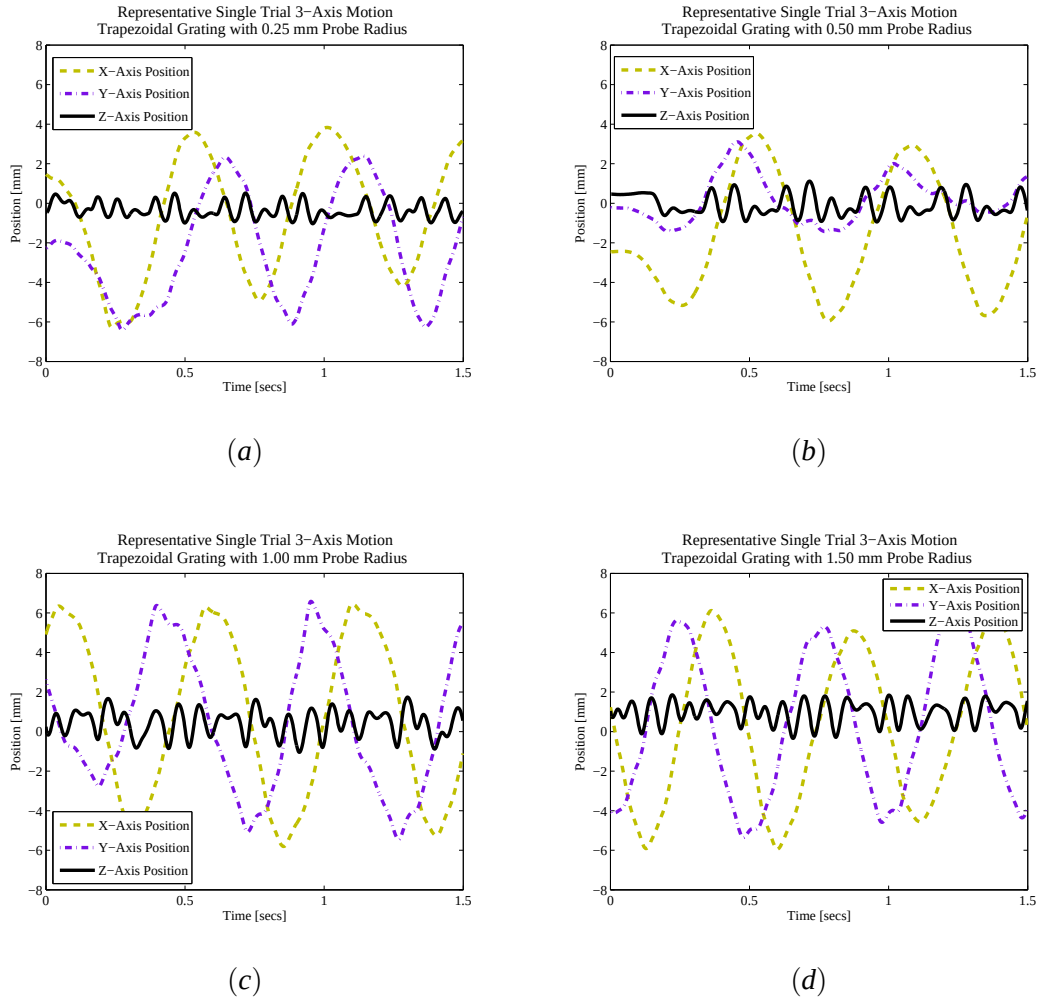


Figure 4.11: Representative example of manipulandum motion along x , y and z axes during a single subject trial on trapezoidal grating texture with a period of 3.96 mm for spherical probe radii of a) 0.25 mm b) 0.50 mm c) 1.0 mm and d) 1.5 mm.

period of 3.96 mm, a period which exceeds the predicted DP for all of the represented probe sizes. At this spacing, there is little difference in the amplitude of motion in the z -axis. It can also be seen that probe size has little effect on how subjects move back and forth on both the x and y axis.

Figure 4.12 shows representative one second samples of the z -axis position from a single subject. Probe size increases across columns and trapezoidal element spacing increases moving down the columns. It is immediately apparent that for all probe sizes, the amplitude of motion increases with increasing spacing. It is also evident that, once the maximum range of z -axis motion has been achieved, further increases in element spacing have little effect. The spacing at which the maximum

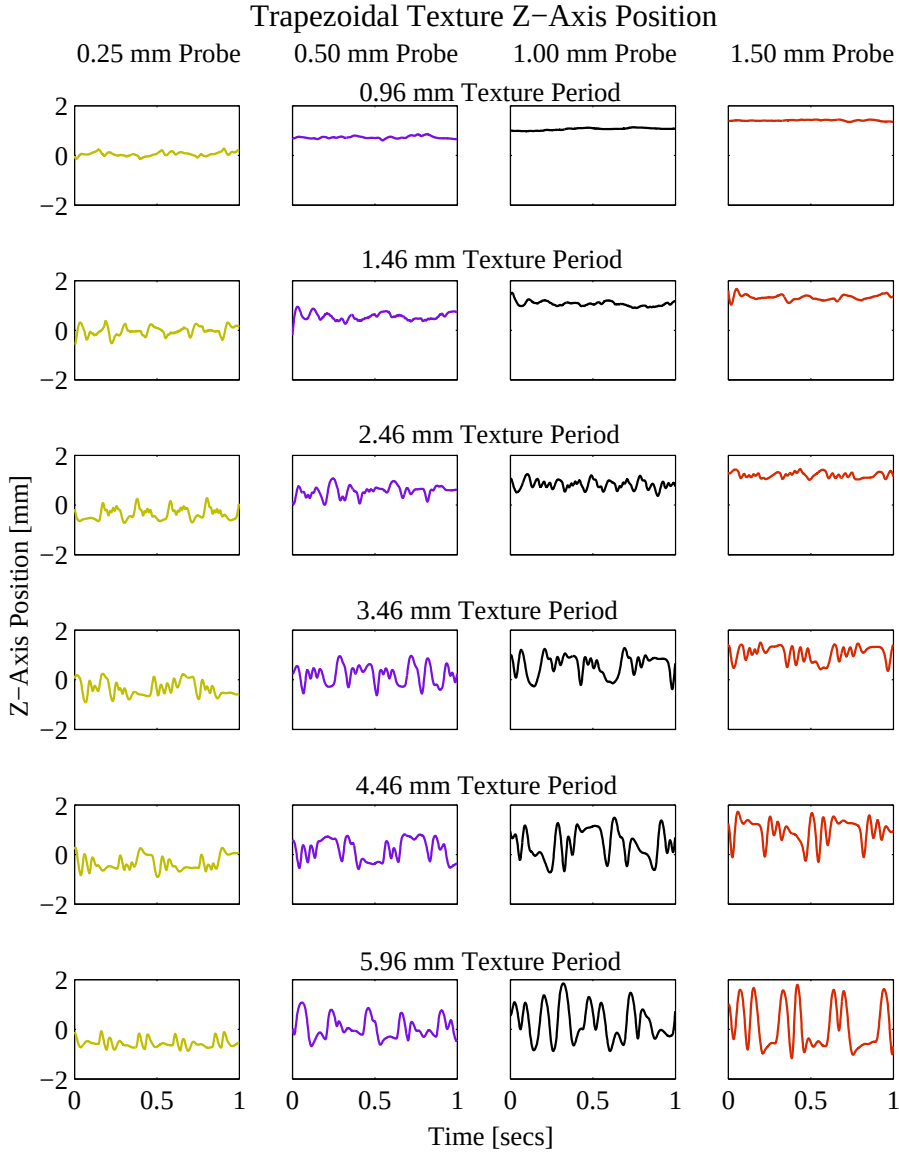


Figure 4.12: Representative trapezoidal grating texture z -axis position samples for four probe sizes covering the full range of texture periods.

range of motion occurs increases as probe size increases. These findings parallel changes in roughness which occur when probe size and element spacing increase. This suggests that the amplitude of motion in the z axis is responsible for roughness perception.

An approximation of the average amplitude of motion in the z axis can be found by taking the standard deviation (σ) of the z -axis position signal. This is effectively the power in the position signal. By determining this value over a range of element spacings, the physical function $P = \Phi(I)$

Trapezoidal Grating Texture: Average Z-Axis Standard Deviation versus Element Period

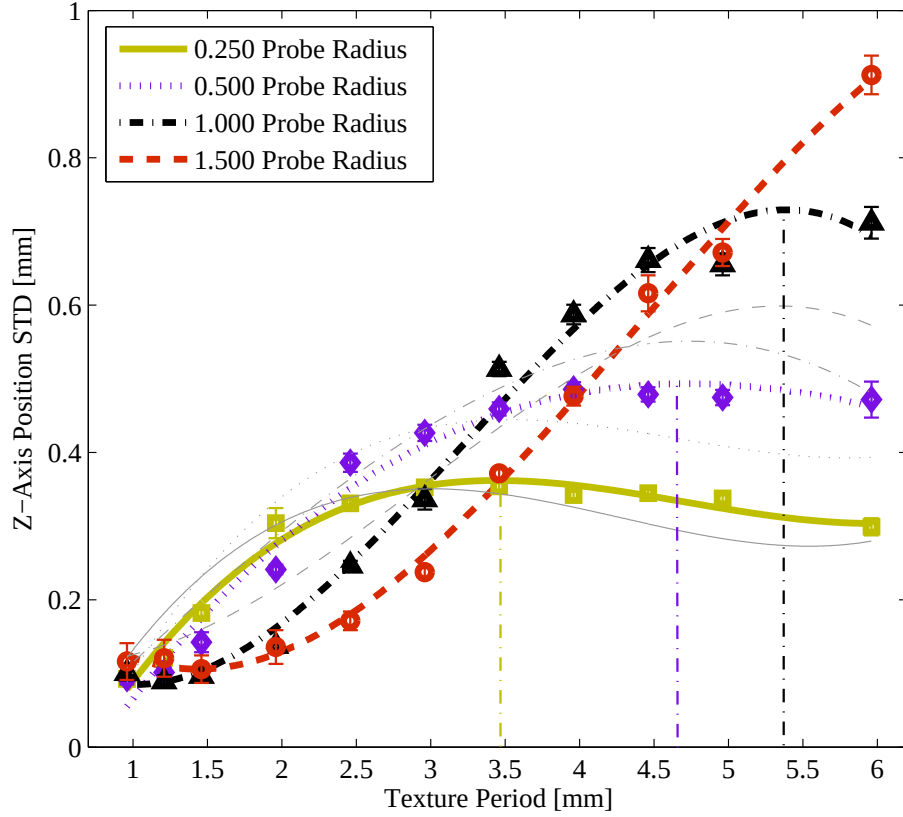


Figure 4.13: Plot of the average over subjects of the standard deviation of the z -axis position signal versus element spacing. A third order fit to the standard deviation data is shown. A third order fit to subject roughness estimates is also shown for comparison. Maxima in the standard deviation fits are shown as vertical lines.

(defined in Section 2.3.3), can be determined. This function relates a physical property to the stimulus, $I = el_T$, used in finding $S = \Psi(I)$, the psychophysical function. Twenty-four subjects had useable MLHD physical data and their individual physical functions were averaged to find an overall $\Phi(I)$ for z -axis position power. A third order fit to $\Phi(I)$ is shown in figure 4.13 for four probe sizes along with third order fits to the corresponding roughness psychophysical functions.

It can be seen that the third order fits to $\Phi(I)$ for the 0.25 and 0.5 mm probe radius appear to match the roughness function well although the larger probes fail to show a similar correspondence. The correlation between $\Phi(I)$ and $\Psi(I)$ is greater than 0.92 for all four probes. This close correlation suggests that the variability of the z -axis position may be what subjects feel as roughness, but it should be noted that a similar correlation does not exist for sinusoidal textures. Higher correlations between roughness and position σ in the trapezoidal grating texture experiment may be due to the

smaller number of texture periods tested and the resulting larger error in the correlation coefficient. It is notable that, in the trapezoidal grating experiment, the point of maximum perceived roughness with a 3rd order fit is considerably smaller than the third order maxima for σ of position. This is true for all probe sizes. Thus, roughness tends to peak prior to the σ of position, further suggesting that it is not the physical property responsible for texture.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-1.27	1.31	3.81	3.00
0.50	-1.52	1.56	4.17	3.54
1.00	-1.37	2.06	4.75	4.74
1.50	-0.53	2.56	7.28	5.34

Table 4.3: The trapezoidal grating texture period at which maximum roughness occurs based on 2nd and 3rd order curves fitted to unlogged normalized roughness estimates averaged across subjects. Curvature of the 2nd order fitted curve and the maximum roughness predicted by the geometric model are also shown. Results are shown for four probe sizes

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-0.03	1.31	4.06	3.45
0.50	-0.03	1.56	4.72	4.72
1.00	-0.01	2.06	9.76	5.39
1.50	0.03	2.56	0.06	7.34

Table 4.4: The trapezoidal grating texture period at which maximum standard deviation (σ) occurs based on 2nd and 3rd order curves fitted to STD estimates averaged across subjects. Curvature of the 2nd order fitted curve and the maximum roughness predicted by the geometric model are also shown. Results are shown for four probe sizes.

In the preceding chapter on sinusoidal textures, probe z -axis mean velocity was investigated as a possible physics property which might be responsible for roughness perception. Correlation between roughness and velocity for sinusoidal textures and point-probes was moderately good although it was not the best correlated property investigated. A similar analysis of trapezoidal grating textures was conducted, finding the z -axis velocity physics function ($\Phi(I)$) for four spherical probe radii.

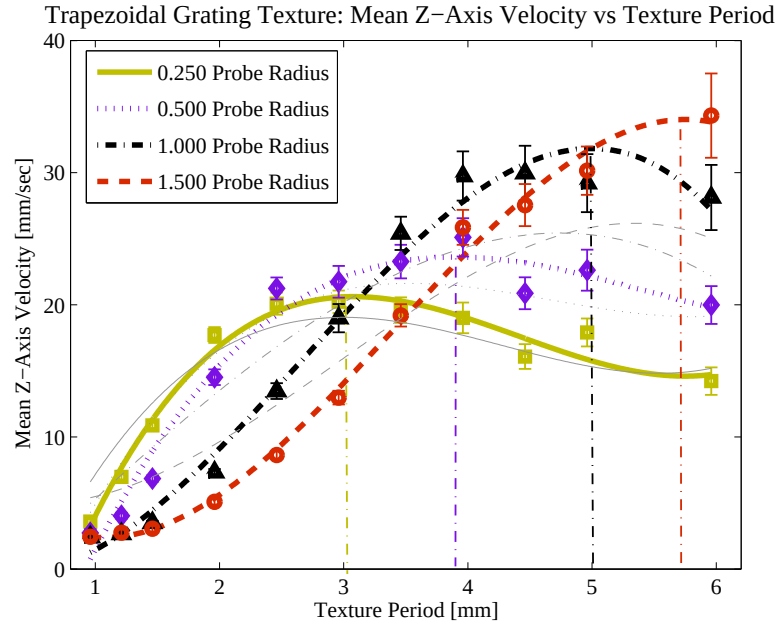


Figure 4.14: Plot of the mean z -axis velocity for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the velocity data and fitted with 3rd order curves are shown as light gray lines.

The velocity functions can be seen in figure 4.14 along with their respective psychophysical roughness functions. As in the case of the σ for z -axis position, the velocity and roughness functions for the smallest probe sizes appear most similar. More significantly, the third order fit maxima for velocity (Table 4.5) and roughness (Table 4.3) are more closely matched than were σ and roughness. This is reflected in the correlation coefficients for velocity and roughness which are all greater than 0.97 (Appendix A, Table A.18). Probe size has a significant effect on the element spacing at which the third order velocity maxima occurs but not on second order maxima (Table 4.6). Probe size also is significant for roughness DP location. For both roughness and velocity, the third order fit therefore seems more appropriate than the second.

Clearly, for trapezoidal textures, velocity is a physics parameter that is tightly coupled to roughness perception. This differs from sinusoidal textures with point-probes and therefore caution should be exercised in declaring velocity to be the primary physical parameter which is actually sensed as roughness. The large number of data points being correlated for sinusoidal gratings, versus the small number for trapezoidal textures (33 versus 11 respectively), suggests that more weight should

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-1.82	1.31	3.81	3.08
0.50	-2.09	1.56	4.23	3.89
1.00	-1.51	2.06	5.51	5.00
1.50	-0.08	2.56	48.36	5.75

Table 4.5: The trapezoidal texture period at which maximum velocity occurs based on 2nd and 3rd order curves fitted to roughness estimates averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of velocity versus spacing is shown. For comparison, the roughness maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	32.00	< 0.0001
2nd Order Maxima	3/92	0.52	> 0.05
3rd Order Maxima	3/92	16.40	< 0.0001

Table 4.6: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to subject velocity estimates.

be given to the former study. Since velocity correlates well with roughness for trapezoidal textures, kinetic energy, derived from velocity is potentially the physical property which is perceived as roughness.

Mean cross-subject z -axis kinetic energy was determined from z -axis velocity as described in Section 3.4.2. A plot of kinetic energy versus texture period can be seen in figure 4.15. Each of the heavy curves represents the physical function for kinetic energy, $\Phi(I)$, determined for a particular probe radius. The roughness functions for respective probe sizes are seen as a light lines. Roughness is normalized to kinetic energy for display purposes.

It can readily be seen that kinetic energy matches roughness poorly when compared to velocity or even the standard deviation of z -axis position. The element spacing at which kinetic energy reaches a maximum is considerably larger than the element spacing at which maximum roughness is achieved for all probe sizes (Table 4.8). A 1-way ANOVA shows that the effect of probe size is not significant for third order maxima (Table 4.8). While the kinetic energy function does not match roughness exactly, it still follows the general shape of the roughness function and correlation

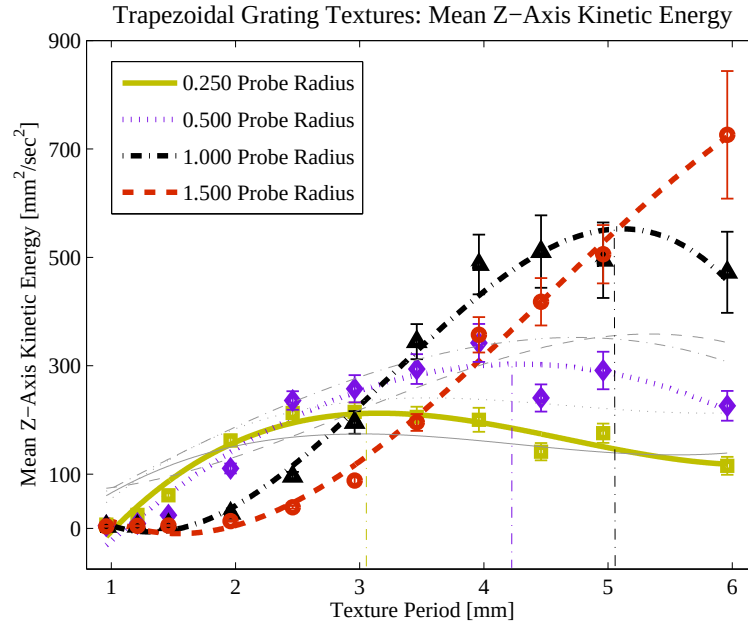


Figure 4.15: Plot of the mean z -axis kinetic energy for trapezoidal grating texture at various texture periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the kinetic energy data and fitted with 3rd order curves are shown as light gray lines.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-25.41	1.31	3.76	3.16
0.50	-30.38	1.56	4.28	4.27
1.0	-14.87	2.06	7.59	5.11
1.5	26.22	2.56	0.51	7.43

Table 4.7: The trapezoidal texture period at which maximum kinetic energy occurs based on 2nd and 3rd order curves fitted to kinetic energy averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of kinetic energy versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

between the physical function for kinetic energy and the psychophysical function for roughness is relatively large with coefficients ranging from 0.91 to 0.97. Based on these results the role of kinetic energy remains unclear with respect to roughness perception. It seems probable that the physical property which results in texture perception is somehow related to kinetic energy but not identical with it.

Factor	DOF	F	p-value
Curvature	3/92	26.74	< 0.0001
2nd Order Maxima	3/92	2.83	< 0.05
3rd Order Maxima	3/92	0.78	> 0.05

Table 4.8: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to kinetic energy.

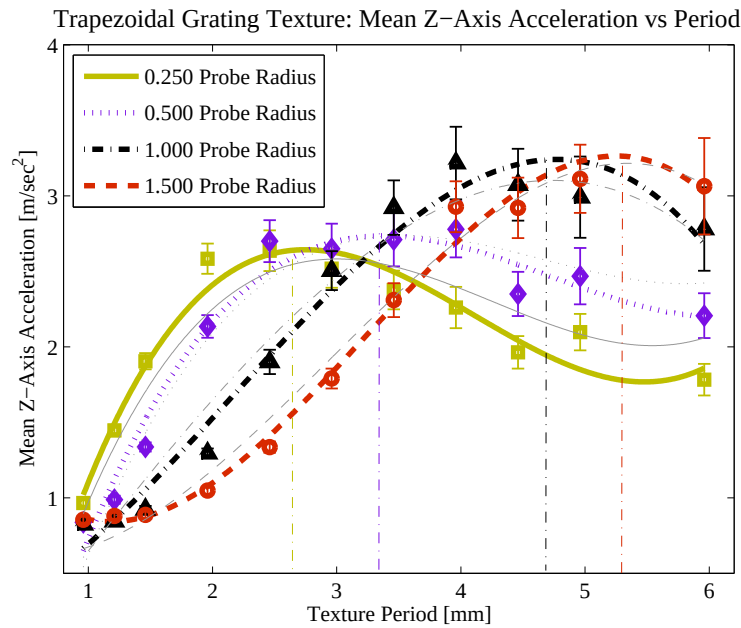


Figure 4.16: Plot of the mean z -axis acceleration for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the acceleration data and fitted with 3rd order curves are shown as light gray lines.

In the sinusoidal texture experiment, acceleration was found to have relatively high correlation with roughness. Figure 4.16 shows a similar close correlation between the second derivative of position and roughness perception.

The spacing at which maximum acceleration occurs is very similar to that at which roughness peaks (Table 4.9) especially for a third order fit. A 1-way ANOVA shows that probe size has a significant effect on the third order acceleration maxima (Table 4.10). The correlation coefficient between acceleration and roughness functions ranges from 0.93 to 0.99.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-170.2	1.31	3.54	2.75
0.50	-210.2	1.56	3.98	3.38
1.0	-171.6	2.06	4.84	4.77
1.5	-51.82	2.56	8.75	5.25

Table 4.9: The trapezoidal texture period at which maximum acceleration occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of acceleration versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	20.33	< 0.0001
2nd Order Maxima	3/92	0.33	> 0.05
3rd Order Maxima	3/92	113.9	< 0.0001

Table 4.10: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to acceleration.

Since acceleration and roughness are relatively well correlated for both sinusoidal texture and trapezoidal texture, acceleration is likely closely related to the physical property underlying roughness perception. For sinusoidal texture, multilinear regression revealed that the total power in the force signal was the most significant contributor to explaining the variance in the roughness data while the contribution of acceleration was negligible. The larger number of element spacings used in the correlation for sinusoidal textures once again suggests that this experiment should be given greater weight than the trapezoidal texture experiment. Thus the close correlation of acceleration with roughness for trapezoidal textures may be secondary to the relationship between force and acceleration.

Mean applied z -axis force, regardless of the probe radius used, is not affected by texture period as can be clearly seen in figure 4.17. However, since the power in the z -axis force signal was found to be the most significant factor explaining the variability in the psychophysical function for roughness it should also correlate well with roughness for all probe sizes used in the trapezoidal texture experiment. The total power in the PSD was determined for the z -axis force signal for each experimental trial. The average total power over subjects for each element spacing was determined

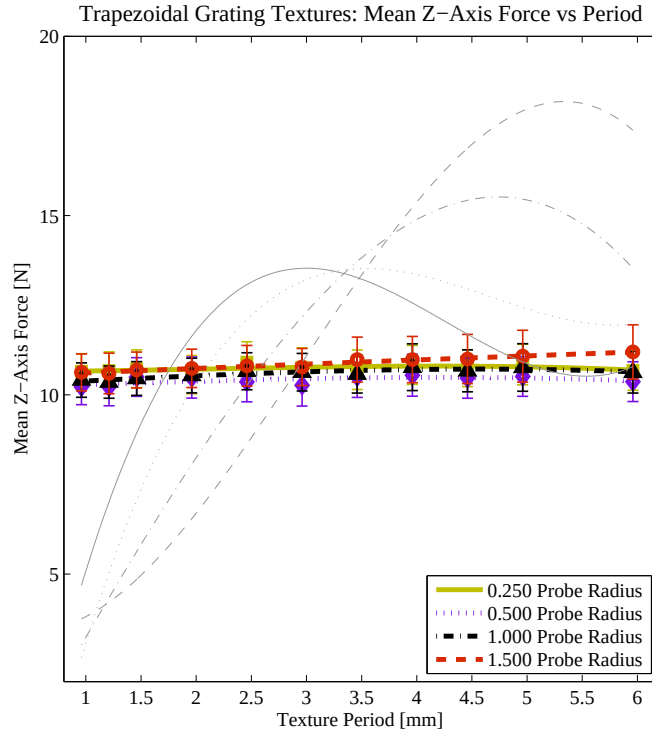


Figure 4.17: Plot of the mean over subjects of the z -axis force for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data. Roughness estimates, normalized to the force data and fitted with 3rd order curves are shown as light gray lines.

and the physics function $P = \Phi(I)$ was determined for each probe size, as described in Section 3.4.4. The plot of $\Phi(I)$ for four probe sizes can be seen in Figure 4.18.

The maxima in the power functions increase with element spacing, following the trend established by the roughness function (Table 4.11). The effect of probe size is significant for third order maxima when tested with a 1-way ANOVA (see Table 4.12). Third order total power maxima generally overestimate roughness function maxima for the same probe size but only by a minimal amount.

Only the smallest two probe sizes show extremely close similarities between the roughness function and the z -axis total power function. Correlation coefficients confirm this with values of 0.97 and 0.98 for the 0.25 and 0.50 mm radius probes and values of 0.94 and 0.95 for the 1.0 and 1.5 mm radius probes (Table A.18). The correlation values are still all quite large, lending support to the idea that total z -axis force signal power is the physics parameter responsible for roughness

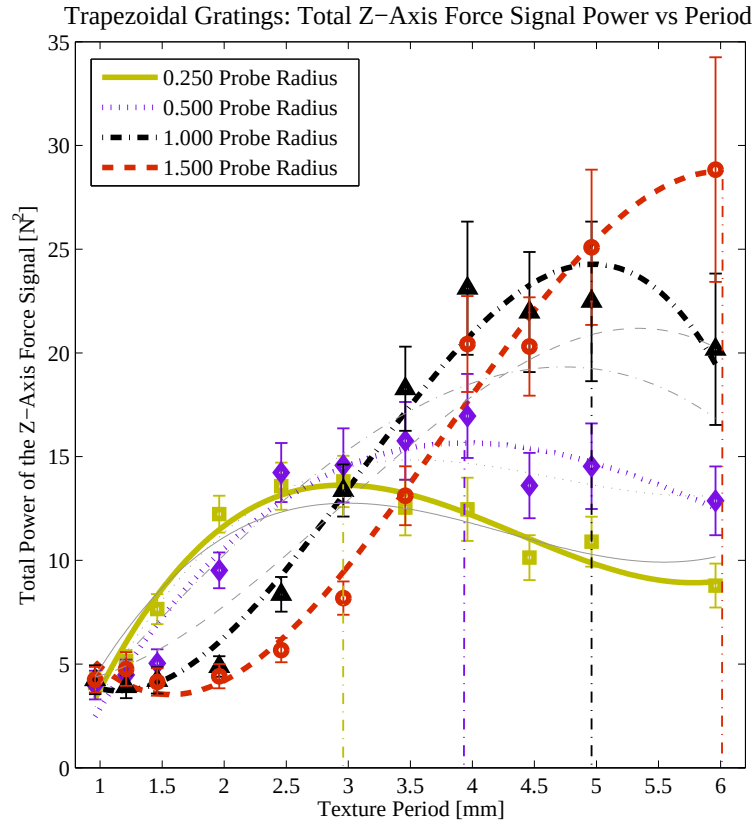


Figure 4.18: Plot of the total z -axis force signal power for trapezoidal grating texture at various periods. The power is the integral of the periodogram of the z -axis force. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the force signal power data and fitted with 3rd order curves are shown as light gray lines.

perception. This hypothesis is reinforced by the fact that the sinusoidal texture experiment determined that the z -axis force signal was the primary factor correlating with roughness. Thus, for two very different textures and probe types, total power in the z -axis force signal correlates well with the psychophysical function for roughness.

By band-limiting the PSD of the z -axis force signal, it is possible to isolate the power experienced by the FA1 and FA2 mechanoreceptors. As described in Section 1.2.2, one or both of these receptors are likely responsible for the perception of roughness with a probe. In the sinusoidal texture experiment, most of the power in the PSD was concentrated in the FA1 bandwidth (5-50 Hz). This bandwidth's physical function ($\Phi(I)$) was better correlated (corr. coeff. 0.65) with the psychophysical function for roughness than that of the FA2's (corr. coeff. 0.45).

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-1.14	1.31	3.66	2.95
0.50	-1.26	1.56	4.17	3.96
1.0	-0.87	2.06	5.95	4.98
1.5	-0.57	2.56	-1.52	6.00

Table 4.11: The trapezoidal texture period at which maximum total power in the force signal occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of total power in the force signal versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	17.84	< 0.0001
2nd Order Maxima	3/92	1.69	> 0.05
3rd Order Maxima	3/92	15.5	< 0.0001

Table 4.12: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to total power in the force signal.

Isolating the same bandwidths of the PSD z -axis force signal for trapezoidal textures and measuring their total power the FA1 and FA2 physical parameter functions can be determined. Figures 4.19 and 4.20 show that both bandwidths follow the psychophysical roughness function relatively well with their third order maxima increasing significantly (see Appendix A and Tables 4.14 and 4.16) with probe radius. This is in contrast to the power in the FA1 and FA2 bandwidths for sinusoidal textures where the FA1 power appeared to lag behind roughness and the FA2 power did not follow it at all. The correlation coefficient between roughness and both bandwidths is thus better for trapezoidal textures ranging between 0.64 to 0.98. It is of note these correlation coefficients show considerable variability implying possible unreliability.

Also of note is the fact that the average correlation coefficient for FA1's is 0.96 while the average for FA2's is 0.87. For both the trapezoidal and sinusoidal texture experiments, the power in the FA1's bandwidth appears to be more highly correlated with roughness perception than the FA2's.

Finally, it is important to note that for trapezoidal textures, the radius of the spherical probe produces a significant effect on the third order maxima in the power of the band-limited force

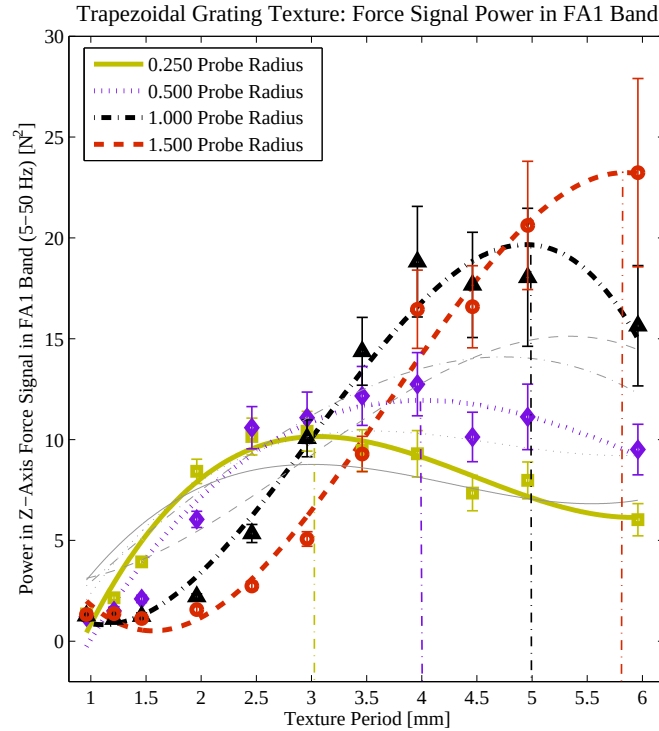


Figure 4.19: Plot of the z -axis force signal power in FA1 band (5-50 Hz) for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the force signal power data and fitted with 3rd order curves are shown as light gray lines.

signal when tested with a 1-way ANOVA (see Tables 4.14 and 4.16). Probe size has therefore been demonstrated to have an effect on the shape of the physical function for all of the parameters tested, particularly their third order maxima.

4.6 Conclusions

The difference between sinusoidal texture explored with a point-probe and trapezoidal texture explored with spherical probes is significant. Roughness perception for sinusoids starts high with small element spacings and then begins a decline which can be defined by Steven's power law with an exponent of -0.8. For trapezoidal textures and spherical probes, for all sizes of probe, roughness begins low and progresses to a high plateau.

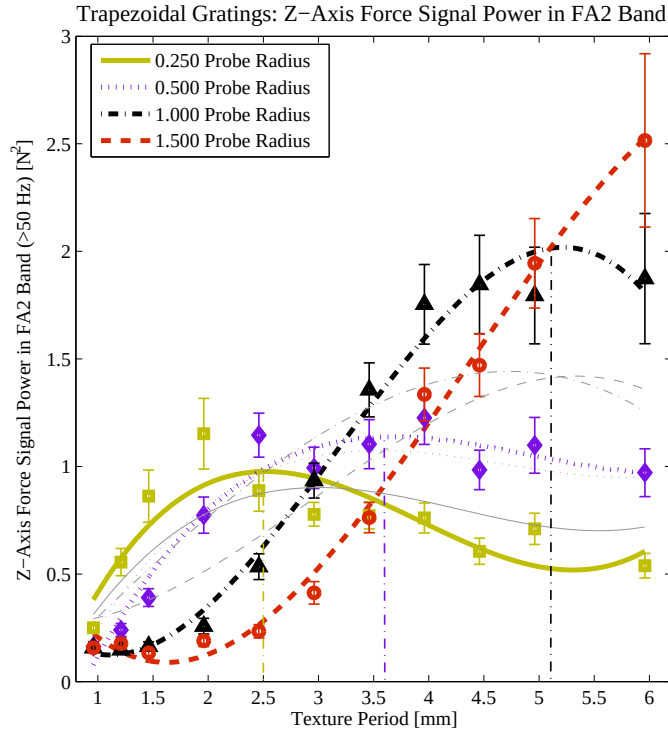


Figure 4.20: Plot of the z -axis force signal power in FA2 band (50-500 Hz) for trapezoidal grating texture at various periods. Four probe sizes are shown. Third order curves are fitted to the data and their maxima are indicated by vertical lines. Roughness estimates, normalized to the force signal power data and fitted with 3rd order curves are shown as light gray lines.

The shape of the psychophysical function (on a log-log plot) for roughness for trapezoidal textures can be fit by a second order function but a third order function is better, while a logistic function seems to achieve the most natural fit. For sinusoids, the best fit seems to be a hockey stick function composed of two linear fits to small (<2 mm) and large (≥ 2 mm) element spacings respectively.

The obvious cause of the differences in roughness perception is the interaction between the geometry of texture and probe. Average force variability, determined to be the principal physical parameter associated with roughness, should increase with the amplitude of z -axis motion and decrease with increasing element spacing. With a point-probe, texture contours can be followed nearly exactly and thus amplitude of motion is invariant and the variation in the force experienced is related to texture period. With a spherical probe, the amplitude of motion is dependent on element spacing, increasing to a maximum as gratings become further apart, and then holding constant. Motion amplitude must therefore be a more important determinant of roughness than increasing texture period.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-1.07	1.31	3.73	3.06
0.50	-1.15	1.56	4.20	4.00
1.0	-0.87	2.06	5.72	4.94
1.5	-0.43	2.56	-2.58	5.84

Table 4.13: The trapezoidal texture period at which maximum total power in the force signal FA1 band (5-50 Hz) occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of total power in the force signal FA1 band versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	17.19	< 0.0001
2nd Order Maxima	3/92	1.22	> 0.05
3rd Order Maxima	3/92	0.63	> 0.05

Table 4.14: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to total power in the force signal FA1 band.

The amount of force variability induced by increasing penetration depth must increase at a faster rate than the decrease in variation resulting from larger spacings. Since the force variability induced by increasing penetration depth will be related to the dynamics of the hand which may vary with time and with the dynamics of the MLHD, the contributions to roughness of penetration depth are likely to be complex and outside the scope of this thesis.

Differences in roughness perception between probes can be attributed to the interaction of probe and texture geometry. The maximum roughness experienced depended on probe size, and the trend in the element spacing at which maximum roughness occurred (increasing with increasing probe size) was predicted by Klatzky's geometric model. The observed third order maxima for roughness were all underestimated by the model as were the maxima (80 percent of range) of logistic fits. The logistic fits were, however, underestimated less. This underestimate is partially explained by adjusting the geometric model to account for probe velocity, changing the model from quasistatic to dynamic.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-0.06	1.31	3.25	2.52
0.50	-0.10	1.56	4.219	3.68
1.0	-0.05	2.06	7.88	5.22
1.5	0.09	2.56	0.57	7.01

Table 4.15: The trapezoidal texture period at which maximum total power in the z -axis force signal FA2 band (>50 Hz) occurs based on 2nd and 3rd order curves fitted to acceleration averaged across subjects. Curvature of the 2nd order fitted curve on a standard plot of total power in the force signal FA2 band versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	22.60	< 0.0001
2nd Order Maxima	3/92	1.28	> 0.05
3rd Order Maxima	3/92	0.65	> 0.05

Table 4.16: Significance of probe size effects, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to total power in the z -axis force signal FA2 band. It should be pointed out that for the third order maxima, if only the smallest three probe sizes are compared, probe size effect is highly significant (2/69, $F=31.7$, $p < 0.0001$).

The trapezoidal texture experiment showed much higher degrees of correlation between all physical parameters and roughness (see Table A.18) than the sinusoid experiment. This inability to distinguish between parameters based on correlation coefficients is likely due to the small number of data points in the trapezoidal experiment when compared to the sinusoidal experiment. Since the physical parameters are, to some extent related to each other, the high correlations for σ of position, velocity, acceleration, power in the FA1 and FA2 force bandwidths, and total power in the PSD of the force signal are not completely unexpected. If the total power in the z -axis force signal had not shown significant correlation, this might have been seen as evidence that force variability was only a significant factor with sinusoidal texture. Since the correlation between roughness and force variability is high in both experiments it lends support to the hypothesis that force variability is the physical parameter which is perceived as roughness regardless of probe-texture geometry.

The relative contributions of FA1 and FA2 receptors to roughness perception are difficult to ascertain from the trapezoidal texture correlation analysis. While the power in the FA2 receptor bandwidth has a slightly lower average correlation with the psychophysical function for roughness than does the FA1, the difference is not large. It is therefore not clear from this experiment which receptor is important. It is possible that both are involved in the perception of roughness. Further experiments with different probe and texture geometries, changes in compliance, and levels of friction, may provide insight into this problem.

Chapter 5

Dithered Conical Textures and Probe Size Effects

5.1 Introduction

In Chapter 4, virtual spherical probes were used to explore trapezoidal gratings. This provided a way to test the hypothesis that the interaction between probe and texture geometry alters a subject's perception of surface roughness. The hypothesis was strongly supported by the finding that the psychophysical function for roughness, $\Psi(I)$, is different for sinusoidal textures with point-probes and trapezoidal textures with spherical probes. In the sinusoid experiment, $\Psi(I)$ was initially flat and then became a decreasing linear function but in the trapezoidal grating experiment, $\Psi(I)$ resembled a third order polynomial or logistic function. Further support for the hypothesis was provided by the observation that the texture period of maximum subjective roughness, or drop point (DP), increases with probe radius for trapezoidal textures, a result predicted by the geometric model for spherical probes (see Section 4.4)[66].

Klatzky *et al.*'s work with real probes on dithered conical textures found that spherical probes had a roughly quadratic psychophysical function, $\Psi(I)$, for roughness and that the period at which the maximum of $\Psi(I)$ occurred increased with increasing probe radius [66]. While a quadratic can be fit to the trapezoidal grating roughness data, the maximum roughness only showed a significant effect from probe size when a third order, rather than a quadratic, fit was used. The trapezoidal grating experiments of Chapter 4 showed trends similar to Klatzky *et al.*'s, with roughness maxima increasing with probe radius. Unfortunately, application of Klatzky's geometric model to the spherical probes used for the experiments of Chapter 4 demonstrated a significant underestimation of roughness DPs determined for all probe radii [66].

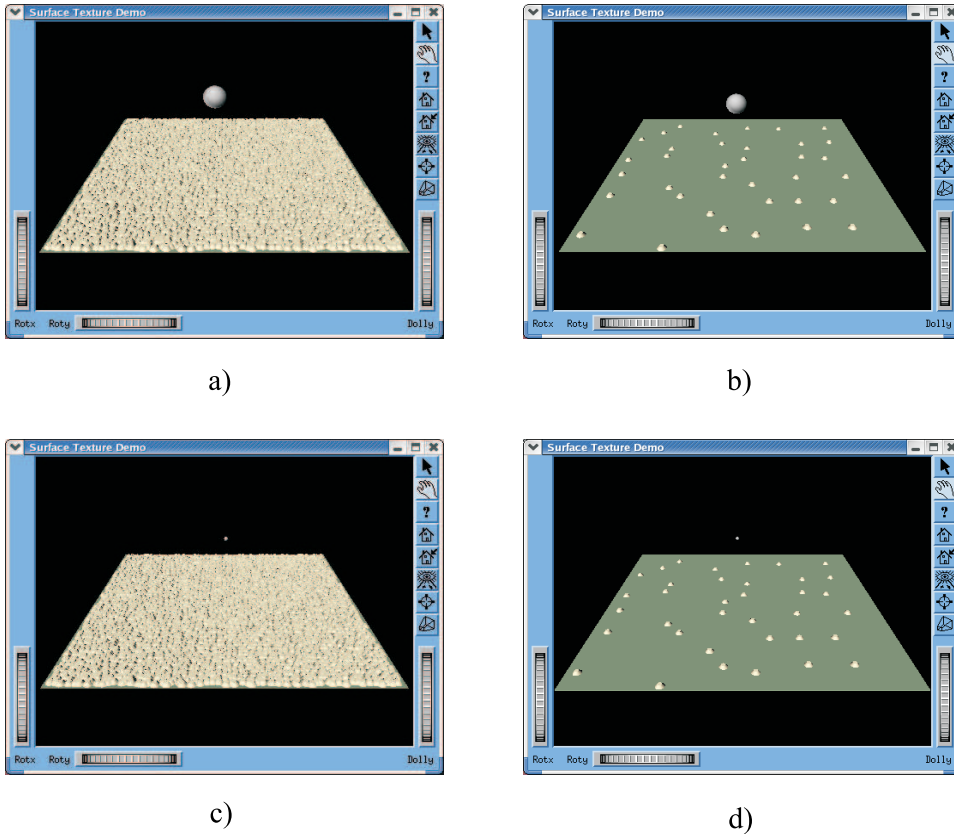


Figure 5.1: Graphical representation of the range of dithered conical texture models for investigation of probe size effects. Textures have element spacings ranging from 0.5 to 5.5 mm and probe radii ranging from 0.25 to 1.5 mm. a) Probe Size = 1.5 mm, Spacing = 0.5 mm, b) Probe Size = 1.5 mm, Spacing = 5.5 mm, c) Probe Size = 0.25 mm, Spacing = 0.5 mm, d) Probe Size = 0.25 mm, Spacing = 5.5 mm.

While the trapezoidal gratings of the previous section were chosen to accurately represent the shape and size of the elements used in Klatzky *et al.*'s experiments, it is important to note that Klatzky's textures were, in fact, truncated cones dithered pseudo-randomly over a surface (see Fig. 5.2) and not gratings [66]. The mean spacing of cones on any of their texture plates was constant but non-periodic. The differences between Klatzky's real dithered conical experiments and this thesis' trapezoidal grating experiments imply that a virtual grating may not be equivalent to dithered cones when it comes to roughness perception.

It seems likely that the periodic nature of the trapezoidal textures somehow alters the perception of roughness by subjects. For example, with a periodic grating, subjects *must* move across elements as they traverse laterally across a surface. The only way a subject can avoid crossing elements is to move the probe exactly parallel to the grating. Even with large element spacings subjects still

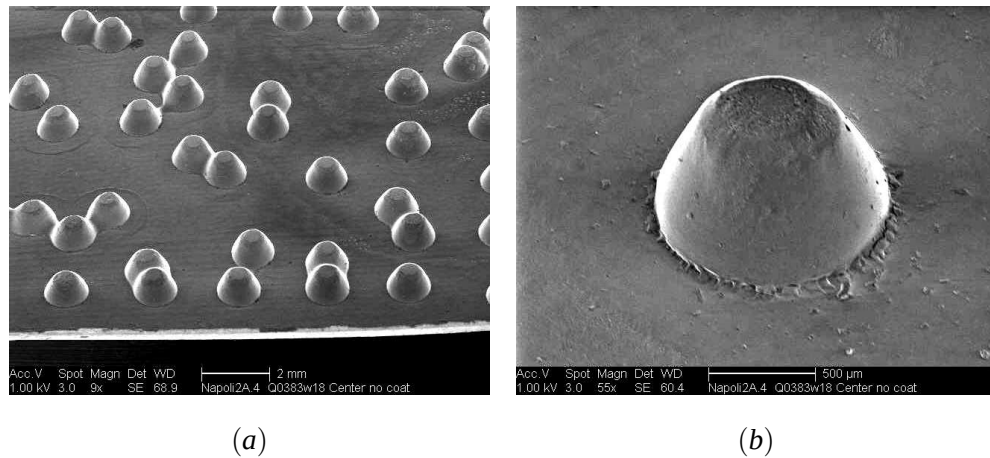


Figure 5.2: Scanning electron micrographs of dithered conical texture plates used in Klatzky *et al.*'s psychophysical experiments [66]. a) Dithered field of conical elements. b) Close-up of single conical element.

encounter the full height of each element they cross. This may account for the plateau in roughness seen with larger spacings and trapezoidal gratings.

If a texture is composed of dithered cones, the amount of free space between elements is quite large. When element spacings are large it is possible for subjects to encounter a cone with the probe and *bounce* off of the side, pinball fashion. They are not forced to traverse the entire height of the cone the way they would be if they were encountering a grating element. This may be the reason why roughness diminishes with large spacings and dithered conical textures. Effectively, the mean free path of the probe can be considered to be larger when a probe interacts with dithered cones than when it traverses a grating.

Similarly, it is possible that the differences between haptic simulations using sinusoidal grating textures [68, 107, 148] and real studies using dithered conical textures [65, 66] (discussed in Section 1.2.2), are related, at least in part, to the periodic grating nature of sinusoidal textures.

It is proposed that virtual texture can produce perceived roughness comparable to real textures if probe-texture geometry is taken into account. This hypothesis is tested in the following experiment. Given a set of virtual pseudo-randomly dithered conical elements and spherical probes (see Figure 5.1), a clear rise and fall of perceived roughness should be seen as mean inter-element spacing increases. The same inverted “U-shaped”, approximately quadratic, psychophysical function, seen in experiments with real dithered conical textures, should also be seen with these virtual textures.

Furthermore, the period at which maximum roughness occurs should increase with increasing probe radius and be comparable in magnitude to real studies with similar geometries.

Once it is established that virtual dithered conical textures have a psychophysical function comparable to real dithered conical textures, the physical parameters determining roughness can be explored using MLHD position and force data. A just-noticeable difference experiment is also described which determines the thresholds at which changes in element spacing result in changes in roughness perception for varying probe radii.

5.2 The Constraint Surface Algorithm for Dithered Conical Textures

It should be possible to reproduce the results of studies which used real dithered conical textures and spherical probes by using the constraint surface algorithm (CSA) as described in Chapter 4 with minor modification. The primary challenge is to extend the constraint surface from a regular series of grating elements to a pseudo-random set of truncated conical elements.

The CSA from the preceding chapter describes the motion of a spherical probe tip across a set of trapezoidal gratings. To extend the model to deal with randomly dithered elements it is first necessary to define their dimensions. The elements will be identical, truncated cones. As seen in Fig. 5.3, each cone has a base radius R_{base} , and a top radius R_{top} . The sides of the cone rise with angle α , to a circular plateau. The height of the cone, C_h , is determined by these parameters as

$$C_h = (R_{base} - R_{top}) \tan(\alpha). \quad (5.1)$$

The conical elements are situated on a smooth surface defined by the (x, y) -plane. In order to generate an apparently random element spacing distribution while preserving the mean spacing distance between cones, their locations are first laid out in a regular square grid pattern. The grid can be represented in memory as a lookup table, and each location in the table corresponds to a region of the (x, y) -plane in the haptic workspace. The entries into the table are initially the (x, y) coordinates of the centers of the regularly spaced elements. Elements coordinates are then dithered by some percentage of their initial spacing using zero-mean white noise. This leaves the mean spacing constant but moves the elements into pseudo-random positions. Examples of dithered conical element surfaces and spherical probes are shown in Fig. 5.1.

The path that a spherical probe will take as it passes over a cone is dictated by the geometry of the probe-element interaction. If a probe of radius R_p travels around a convex corner that has

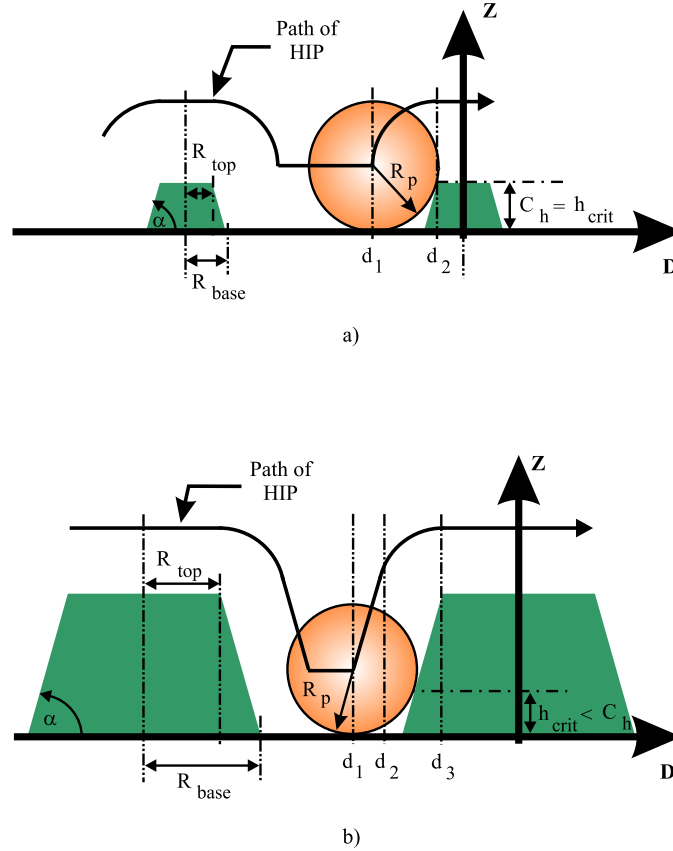


Figure 5.3: a) Large spherical probe moving over a smaller cone where first contact occurs at the cone's upper lip. The critical height of contact, h_{crit} , based on the probe radius and angle of the cone, is equal to the cone height, C_h . b) Smaller spherical probe moving over a larger cone where first contact occurs below the cone's upper lip ($h_{crit} < C_h$).

greater curvature than the sphere itself, it moves along an arc with radius R_p . Otherwise, it moves a distance R_p from the surface and parallel to it. The probe path is therefore governed by a set of piece-wise continuous functions. The inflection points between the functions are determined by the radius of the probe and the shape of the cone.

In determining the probe path, it is first necessary to locate the probe with respect to the nearest cone element. The center of the probe is mapped onto the haptic interaction point (HIP). The cartesian distance in the (x, y) -plane, d , is found from the center of the probe to the center of the nearest cone. The nearest cone is found by using the probe's current (x, y) location as an index into the pre-computed lookup table which records the dithered position of all cones in their initial undithered rectangular grid. A fast search of the lookup location and its nearest neighbors in the table quickly determines the closest element. If the probe is farther than d_1 , the point of initial

contact, from any cone, the height of the HIP above the surface, z_{des} , will simply be that of the probe radius itself. The location of d_1 , and other points of inflection in the probe path, are determined from the probe radius and cone side angle and are defined as distances from the nearest cone element center.

A spherical probe may either make first contact with a cone at its upper edge as shown in Fig. 5.3a or at the point along the cone's leading edge where the tangent to the sphere's surface is equal to α as seen in Fig. 5.3b. This critical height of the first contact, h_{crit} , is found as

$$h_{crit} = R_p(1 - \cos(\alpha)), \quad (5.2)$$

and is used to divide probe-cone contacts into two cases. The first case (Fig. 5.3a), in which $C_h \leq h_{crit}$, has two probe path inflection points, d_1 and d_2 , which are found as:

$$d_1 = R_{top} + \sqrt{C_h(2R_p - C_h)}, \quad (5.3)$$

$$d_2 = R_{top}. \quad (5.4)$$

In this case, the probe's distance, d , from the center of the nearest cone dictates its height, z_{des} , above the (x, y) -plane as follows:

$$d \geq d_1 : z_{des} = R_p, \quad (5.5)$$

$$d_2 \leq d < d_1 : z_{des} = C_h + \sqrt{R_p^2 - (d - R_{top})^2}, \quad (5.6)$$

$$0 \leq d < d_2 : z_{des} = C_h + R_p. \quad (5.7)$$

The second case, in which $C_h \geq h_{crit}$ (Fig. 5.3b), has three probe path inflection points

$$d_1 = R_{base} + R_p \sin(\alpha) - h_{crit} \cot(\alpha), \quad (5.8)$$

$$d_2 = R_{top} + R_p \sin(\alpha), \quad (5.9)$$

$$d_3 = R_{top}. \quad (5.10)$$

In this case, the probe's height, z_{des} , above the x, y plane is determined by d as:

$$d \geq d_1 : z_{des} = R_p, \quad (5.11)$$

$$d_2 \leq d < d_1 : z_{des} = \frac{R_p + (R_{base} - d) \sin(\alpha)}{\cos(\alpha)}, \quad (5.12)$$

$$d_3 \leq d < d_2 : z_{des} = C_h + \sqrt{R_p^2 - (d - R_{top})^2}, \quad (5.13)$$

$$0 \leq d < d_3 : z_{des} = C_h + R_p. \quad (5.14)$$

The calculated heights (z_{des} above the (x, y) -plane) are used to constrain the MLHD's motion along the z axis. It is free to move above the constraint surface or along it in x and y .

It should be noted that the probe only ever interacts with a single cone; that which is closest to it. If the spherical probe is in contact with two cones at once, the desired height above the (x, y) -plane is the same as if only one cone were in contact. This occurs because the cones and the probe are symmetric and all cone shapes are identical.

5.3 Roughness Magnitude Estimation Experimental Design

The constraint surface algorithm, as modified above, was used to generate a set of virtual dithered conical textures. The size and shape of the conical texture elements was selected to allow comparison with previous studies of real textures [66] and the preceding study of trapezoidal gratings (see Chapter 4). Conical elements were kept consistent with comparable dimensions of the trapezoidal gratings of Chapter 4 such as element height ($C_h = el_h = 0.42$ mm) and side angle ($\alpha = 53^\circ$). The base and top radii ($R_{base} = 0.52$ mm and $R_{top} = 0.23$ mm) of the dithered texture's truncated conical elements were made equal to half of the base and plateau widths respectively of the previously used trapezoidal grating elements. Element size was constant throughout the experiment.

Element spacing, el_T , is determined from the mean distance between element centers. As stated in section 5.2, elements are laid out on a grid at their desired el_T . They are then randomly moved from their initial location by up to 40 percent of their initial spacing using zero-mean white noise. This results in a pseudo-random distribution which maintains their original mean spacing.

Eleven element spacings (0.5, 0.75, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5 and 5.5 mm) were used. Finer sampling was used at smaller texture spacings to detect potentially subtle results which, it was suspected, might occur in these ranges. The range of spacings was similar to the range of spacings explored in the literature [66, 68, 74]. The chosen range was subject, at its upper end, to

the limitations of the MLHD workspace, and at its lower end, to the MLHD's position bandwidth (see Section 4.2).

Four spherical probes with radii of 0.25, 0.5, 1.0 and 1.5 mm, were used by subjects to explore the eleven texture spacings. The probe sizes were chosen to allow comparison with previous literature on real probes [66, 74, 79]. The probe sizes selected also had theoretical roughness maxima which, according to the geometric model (see Section 4.4) fell within the selected range of texture spacings. The range of spacings and probe sizes therefore allowed comparison of real, virtual and predicted roughness maxima.

Four probe radii and eleven spacings generated 44 probe-spacing combinations. Subjects encountered each of the 44 combinations 3 times. In the preceding experiment on trapezoidal gratings, subjects encountered four blocks of trials, each block consisting of a single probe size matched against all element spacings, with 3 iterations for each probe-spacing match-up. Since the subject encountered only a single probe size within a block, inter-block comparisons of the roughness magnitude were not valid, since subjects might have used different scales between blocks.

In the dithered cone experiment, to allow valid comparison of roughness magnitude between probes, blocking was not used and the 132 trials (44 probe-spacing combinations performed 3 times each) were presented in random order. This ensured that subjects used the same scale throughout the experiment to gauge roughness and thus direct comparisons of roughness magnitude could be made between different probe sizes.

Twenty-four undergraduate subjects from the Carnegie Mellon psychology department's experimental subject pool took part in roughness magnitude estimation experiments. Of these subjects, 7 were female and 17 were male. Four subjects were left-handed and performed the experiment with their non-dominant (right) hand. The others were all right-handed by self-report.

Subjects were seated approximately 500 mm from a graphical display, which was used to enter the roughness estimates, with the MLHD on their right-hand side. The texture was only displayed haptically. White noise, played through headphones, ensured that audio cues were not available to help subjects discriminate between textures.

Subjects were notified that they would encounter the textures as a series of trials. Trials were presented in two blocks: a demonstration block and an experimental block. The demonstration block consisted of 24 trials, in which six texture spacings, spanning the range of 0.5-5.5 mm, and all four probe sizes were displayed. This allowed subjects to develop an internal scaling system for the range of textures which they were about to encounter. No actual magnitude estimation was made

during the demonstration period. After the demonstration block, the actual magnitude estimation began. Subjects entered a numeric value using a computer keyboard and were informed of their progress by a reported trial number. They received no other feedback on performance. Subjects were not instructed how to feel the texture and were given no restrictions on time. Although experiments were slated to run for one hour, most subjects finished in much shorter time frames.

Subjects were told that they could assign roughness estimates to any positive range of numbers but that larger numbers were to reflect larger values of roughness and smaller numbers were to represent smaller values of roughness. They were specifically asked not to use 0 or negative numbers.

For this experiment the MLHD proportional gains were set to nominal values of 10 N/mm in translation and 25 Nm/radian for orientation. This provided a relatively stiff surface and prevented, to a large extent, rotation of the manipulandum. Only z -axis forces were actively generated by the desired z -axis position and rotation was therefore restricted. Derivative gains for the MLHD were set to 0.04 N/mm/s in translation and 0.5 N/radian/s for orientation to prevent instability. A feedforward force was also supplied in the z axis to minimize the flotor's weight.

5.4 Dithered Conical Textures and Roughness Perception

Previous psychophysical studies of virtual textures demonstrate a variable linear relationship between element spacing and perceived roughness [68, 91, 107, 147]. The psychophysical function, $\Psi(I)$, determined in Chapter 3 for sinusoidal textures, is a decreasing linear function for texture spacings greater than 1 mm. The trapezoidal grating textures with spherical probes studied in Chapter 4 show a $\Psi(I)$ that is best fit by a logistic or third order curve. None of these virtual texture experiments shows the same inverted “U”-shaped $\Psi(I)$ found by Klatzky *et al.* when real textures are explored with spherical probes.

There are two possible causes of this difference in the form of $\Psi(I)$. First, it is possible that current haptic hardware is incapable of adequately rendering some important component of a texture's roughness. Roughness perception, for example, might depend on a complex high frequency signal which can not be replicated by existing haptic hardware. Second, it is possible that the model used to render virtual texture fails to capture characteristics essential to the perception of roughness.

The dithered cone texture experiment is an attempt to determine if careful modeling of the geometry of probe-texture interaction, rendered using state-of-the-art haptic hardware, can demonstrate the same kind of roughness perception $\Psi(I)$ seen in experiments with real textures.

In this experiment, subjects explored dithered cones with spherically-tipped probes, estimating roughness magnitude for different element spacings. A second order fit approximates the roughness magnitude estimation data well, although, as expected, a third order fit has a smaller average R^2 value (see Figure 5.4 and Appendix A, Table A.19). The $\Psi(I)$'s for each probe radii shown in Figure 5.4 are the averages of the normalized $\Psi(I)$'s of individual subjects for that probe size (determined using the procedures outlined in Section 2.3.2).

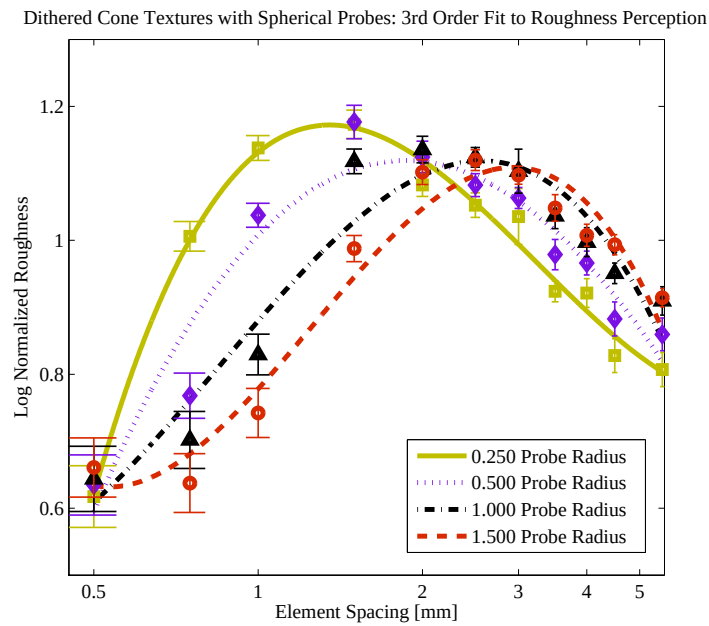
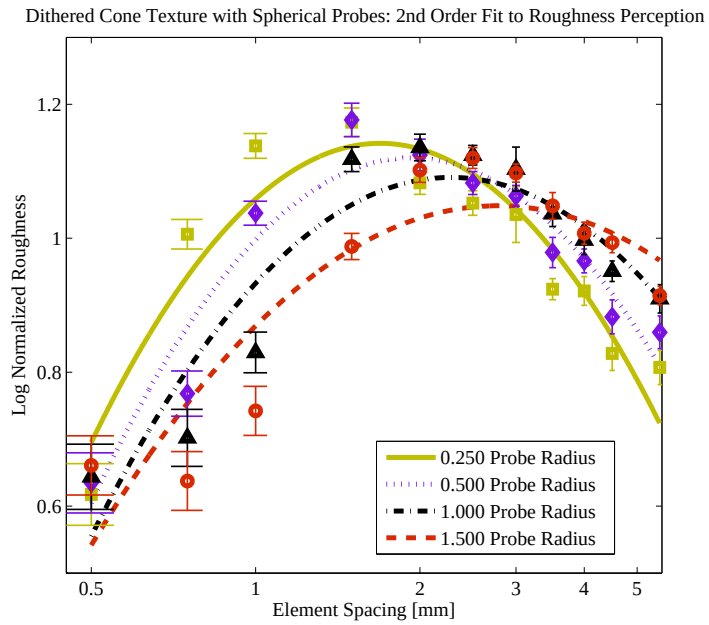
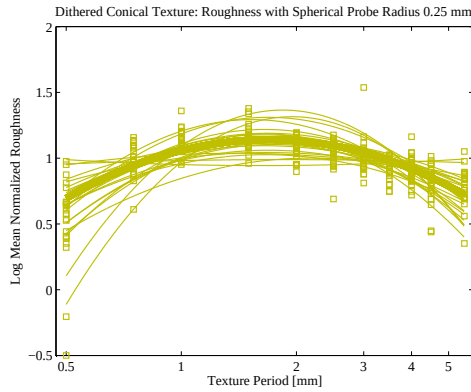
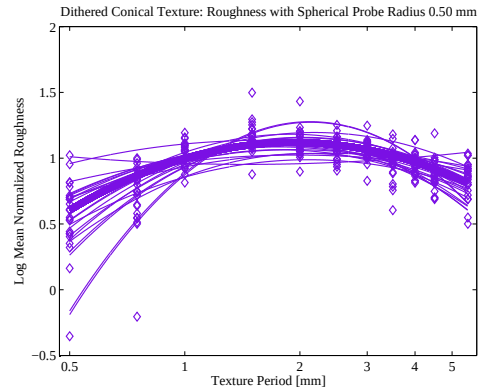


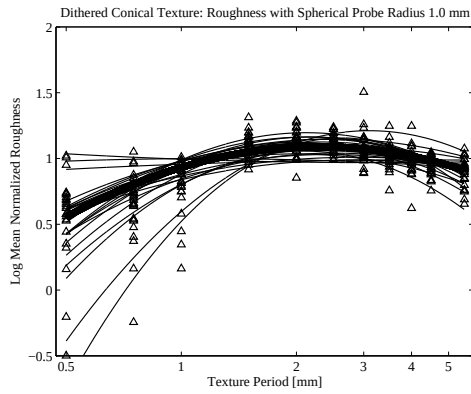
Figure 5.4: a.) Second order fit to mean normalized roughness estimates of dithered conical textures at 11 spacings explored with spherical probes. b.) Third order fit to mean normalized roughness estimates of dithered conical texture at 11 spacings explored with spherical probes.



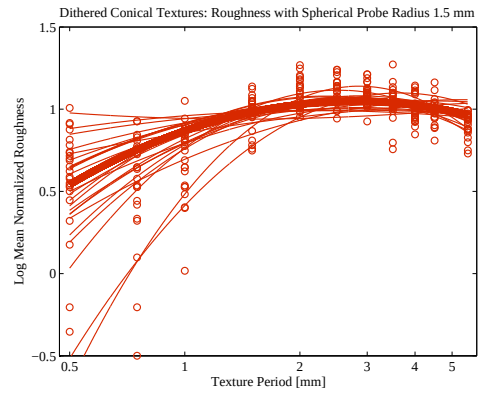
(a)



(b)



(c)



(d)

Figure 5.5: Thin lines represent individual subject roughness estimates fitted with 2nd order curves in a log-log plot. The 2nd order fit to the mean data is plotted as a thick line. Each plot represents a single probe radius as follows: a) 0.25 mm b) 0.50 mm c) 1.0 mm and d) 1.5 mm.

While the individual roughness perception functions are quite variable, Figure 5.5 shows that the vast majority of them are well fit by a quadratic curve. The fitted quadratics are similar to those found by Klatzky *et al.* using real dithered conical textures and spherical probes [66]. They bear little resemblance to the linear functions found with virtual sinusoidal haptic textures in previous studies [68, 91, 107, 147] and in Chapter 3 of this thesis.

Clearly, probe-texture geometry plays an important role in determining the shape of the psychophysical function for roughness. It is no surprise that studies which compare virtual sinusoids to

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-1.59	1.31	1.69	1.35
0.50	-1.50	1.56	1.93	1.86
1.00	-1.23	2.06	2.28	2.57
1.50	-0.92	2.56	2.77	2.93

Table 5.1: The maxima of dithered conical texture roughness estimates based on 2nd and 3rd order curves in a log-log plot (antilog values shown). Curvature of the 2nd order fitted curve on a log-log plot of roughness versus spacing is shown. For comparison, the maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

real dithered cones fail to find similar $\Psi(I)$'s. The fault lies not with the haptic device or the virtual nature of the texture but rather with the choice of texture model.

Factor	DOF	F	p-value
Curvature	3/92	3.06	< 0.05
Maximum Roughness	3/92	0.21	> 0.05
2nd Order Maxima	3/92	25.39	< 0.0001
3rd Order Maxima	3/92	22.61	< 0.0001

Table 5.2: Significance of probe size effects, determined using a 1-way ANOVA on curvature, maximum roughness (curve height) and maxima of a 2nd and 3rd order fit to roughness estimates.

The element spacings of maximum roughness predicted by the geometric model (see Section 4.4) along with the locations of the maxima of second and third order fits to experimentally determined subjective roughness, can be seen in Table 5.1. A 1-way ANOVA shows that the maxima of both the second and third order fit differ significantly with respect to probe radius as does the second order curvature. The maximum subjective roughness reported by subjects, however, is not significantly affected by probe radius.

Increasing probe radius clearly increases the spacing at which subjects feel maximum roughness. This is predicted by the geometric model. The underestimation of the point of maximum roughness by the model, can, once again, be explained with reference to the model's quasi-static nature (see Section 4.4). Since the probe velocity is not zero, the spacing required for the probe to hit the inter-element valley floor is larger than that predicted by the quasi-static model. The average

error (DP_{err}) is +0.30 mm for second order maxima and +0.31 mm for the third order maxima. Using a mean planar velocity, of 49.06 ± 3.34 mm/sec, found by averaging planar velocity over all subjects and conditions during the dithered conical element experiment, together with the element height, el_h , of 0.42 mm, and Equation 4.16, the predicted error in the quasi-static model DP is +0.45 mm. The DP 's for virtual dithered cone texture are thus very close to the revised geometric model's predicted values.

Previous studies with real textures have found that probe velocity affects the location of maximum roughness, causing it to increase [66, 77]. This is consistent with the predictions of the revised geometric model since higher velocity will result in a larger DP_{err} .

The locations of virtual dithered cone texture DP s are very similar to those found for identical real textures. Klatzky *et al.* found maxima of 1.70, 2.23 and 2.98 mm for probes with radii of 0.5, 1.0, and 1.5 mm respectively [66]. These values are corrected to reflect spacings taken from element center to element center, as opposed to the so-called HV spacing between element edges used by Klatzky *et al.* This allows direct comparison to the results of this thesis, as seen in Figure 5.6. The mean difference between the element spacing at which Klatzky's real roughness $\Psi(I)$

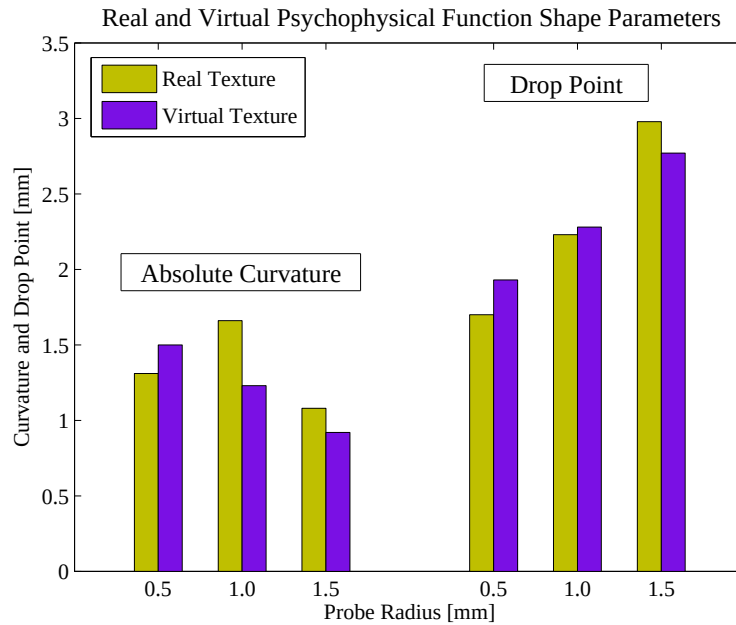


Figure 5.6: Comparison of the curvature and maxima location (drop points) of the psychophysical function for roughness ($\Psi(I)$) for real and virtual spherical probes on dithered conical textures. Real data are taken from Klatzky *et al.* [66].

maxima occurred, and the geometric model's predictions, is +0.24 mm. The mean difference between their real maxima location data and the virtual roughness maxima location in this experiment is -0.02 mm. The mean absolute difference is 0.16 mm. This similarity in roughness maxima location demonstrates that, with appropriate modeling of probe-texture geometry, virtual roughness perception functions can be made nearly identical to real ones.

In the dithered conical texture experiment, the absolute curvature of $\Psi(I)$ was found to steadily decrease with probe size (Table 5.1). This effect of probe size on curvature was found to be significant using a 1-way ANOVA (Table 5.2).

Curvature is a measure of the sensitivity of roughness perception to changes in spacing. Large absolute curvature implies large changes in subjective roughness over a fixed range of spacings while small absolute curvature suggests small changes in roughness over the same range of spacings. Thus, as probe size increases and $\Psi(I)$'s curvature decreases, the sensitivity of subjective roughness to element spacing decreases. The reasons for this effect are unclear but may be related to the smoother path followed by the larger spherical probes over the texture elements. Real dithered conical textures did not demonstrate this monotonic trend although absolute curvature for the largest of three probe sizes (1.5 mm radius, curvature = -1.08) was smaller than that for the smallest (0.5mm radius, curvature = -1.31) [66]. The average absolute difference between real (determined from Klatzky *et al.*'s HV data) and virtual texture $\Psi(I)$ curvatures is 0.26.

Looking back at Figure 4.3 it can be seen that if element shape remains fixed, a larger spherical probe will travel around sharp element corners following a path that has the same curvature as the probe radius. Thus, changes in z -axis probe position for large probes occur more gradually than for small probes, which have to traverse paths with tighter curves. Since roughness perception appears, based on the experiments of Sections 3.4 and 4.5, to be related to z -axis force variability, increased probe size should lead to lower perceived roughnesses for equivalent penetration depths. Maximum roughness at the DP should therefore decrease as probe size increases. While this trend is clearly visible on the plot of second order fits to $\Psi(I)$ (Fig. 5.4), a 1-way ANOVA did not find it to be significant. The sample size of this experiment (24 subjects) seems to have been insufficient to determine if this subtle effect actually exists. Klatzky *et al.*'s findings for real texture probe size effects on relative roughness magnitude were also indeterminate [66] but their experiment was blocked by probe size, rendering comparison of roughness maxima impossible to interpret.

The results of this experiment demonstrate that near equivalence between virtual and real roughness perception can be achieved using a MLHD and an algorithm which accounts for probe-texture geometric interaction.

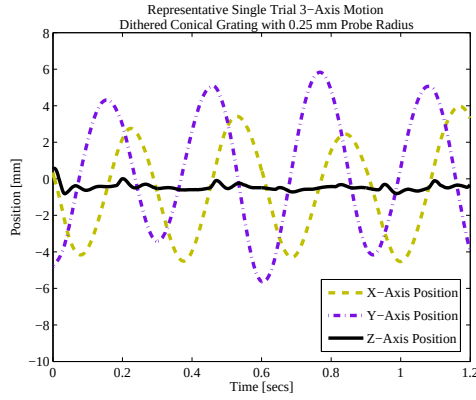
5.5 Dithered Conical Textures and the Physics of Roughness Perception

The physical property most likely to underly roughness perception was determined to be, in Section 3.4 for sinusoidal grating textures, the total power in the force signal, a measure of force variability. Section 4.5 used trapezoidal gratings and supported the idea that force signal power was experienced as roughness, although several other physical properties were also strongly correlated with the magnitude of perceived roughness.

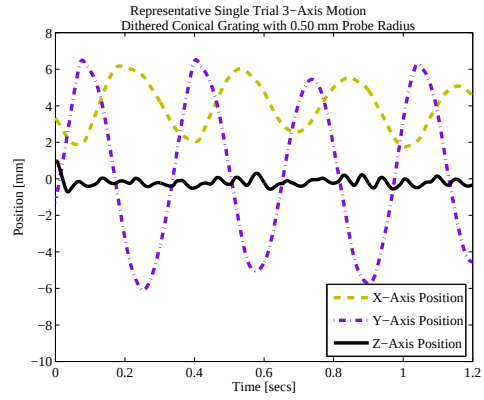
In this section, the manipulandum position and MLHD force output signals, recorded during the preceding subject magnitude estimation trials using dithered conical textures, are examined to determine their relation to perceived roughness. The analysis proceeds along the same lines as that of Sections 3.4 and 4.5.

Figure 5.7 shows a 1.2 second representative example of manipulandum position recorded at 1000 Hz in the x , y and z axes for each of the four probe sizes. It is seen that motion in the x and y axes is considerably larger than that in the z axis. Motion in the x and y axes is primarily induced by subject hand motion while that in the z axis is a result of interaction between the probe and the virtual texture.

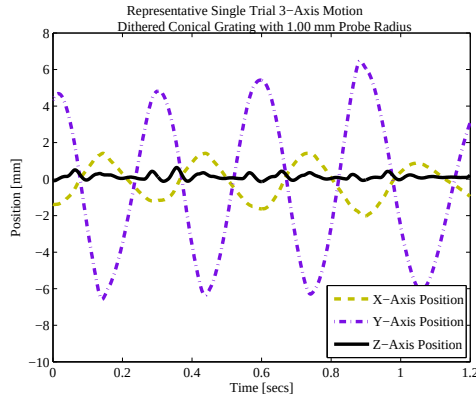
In the experiments using sinusoidal and trapezoidal grating textures, subjects' motion is largely oriented perpendicular to the long axis of the grating elements. Presumably subjects are attempting to maximize the number of elements traversed. Since the dithered conical texture is anisotropic, subjects encounter roughly the same number of texture elements regardless of the direction in which they move. Subjects can therefore align their motion along any axis and get the same effect. An example of this can be seen in Figure 5.7 where, for the 0.5 and 1.0 mm radius probes, motion along the y axis is much larger than along the x axis. For the trapezoidal gratings of section 4.5, the all-subject mean σ for x -axis position was 3.61 mm while for the y -axis it was 3.28 mm, indicating that motion is aligned more along the x axis than the y . For dithered cone textures, this is reversed with all-subject mean σ 's of 3.12 and 3.72 mm for x and y axes respectively, indicating an overall tendency to align motion more along the y axis than the x .



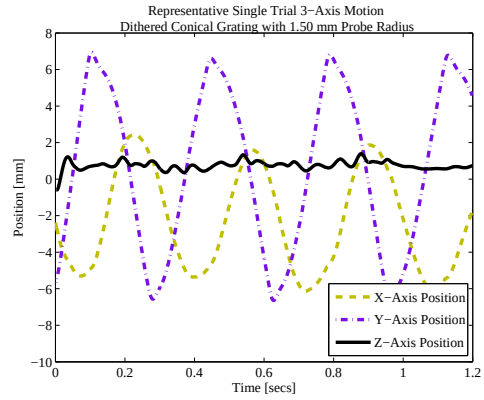
(a)



(b)



(c)



(d)

Figure 5.7: Representative example of manipulandum motion along x -, y - and z -axis during a single subject trial on dithered conical textures with a period of 3.50 mm for spherical probe radii of a) 0.25 mm b) 0.50 mm c) 1.0 mm and d) 1.5 mm. Subject was a right-handed male.

Motion in the z axis is a result of the interaction between the geometry of the virtual probe and texture. Figure 5.8 shows representative recording samples of z -axis position across the range of texture spacings for each of four probe sizes. It can be observed that the range of motion initially increases with texture spacing and then decreases again, regardless of probe size. The element spacing at which maximum motion range is achieved, however, varies with probe size, growing larger as probe size increases.

The physical function, $\Phi(I)$, was determined according to the same procedures used in Section 3.4, for a wide range of physical properties potentially associated with roughness perception. This

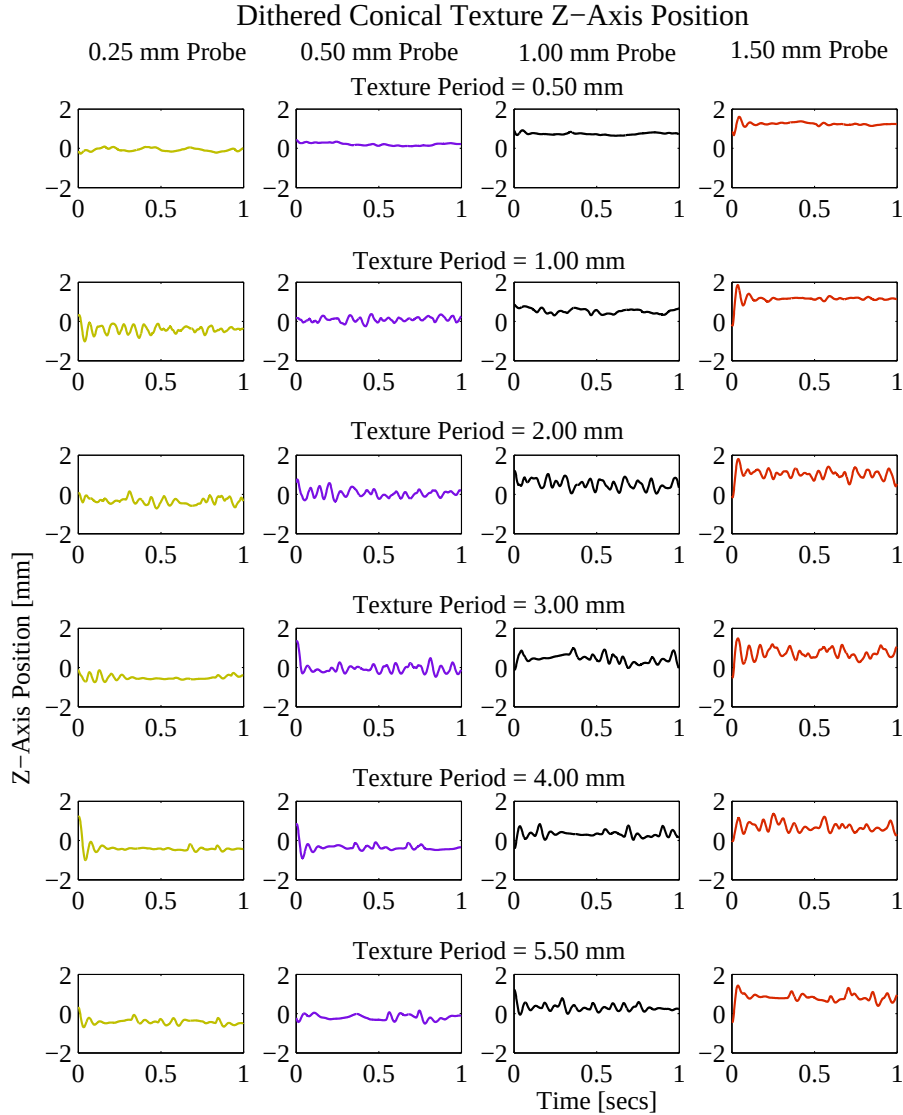


Figure 5.8: Representative samples of z -axis position for the range of probe sizes (0.25-1.5 mm) and texture spacings (0.5-5.5 mm) used in the dithered conical texture probe size experiments.

function associates the magnitude of a physical property (*i.e* manipulandum z -axis velocity) with inter-element spacing based on real-time measurements made during magnitude estimation trials. It is the counterpart of $\Psi(I)$, the psychophysical function for roughness, which associates subjective roughness with inter-element spacing. Correlation coefficients are found between each property's $\Phi(I)$ and the roughness $\Psi(I)$ for corresponding probe sizes. A high degree of correlation between

the $\Phi(I)$ of a physical property and $\Psi(I)$ is assumed to be evidence of a causal relationship between them (see Section 1.3).

	0.25 mm Probe		0.5 mm Probe		1.0 mm Probe		1.5 mm Probe	
Parameter	Corr. C.	p	Corr. C.	p	Corr. C.	p	Corr. C.	p
Mean Position	0.02	> 0.05	-0.32	> 0.05	-0.54	> 0.05	-0.68	< 0.05
Velocity	0.98	< 0.0001	0.99	< 0.0001	0.99	< 0.0001	0.99	< 0.0001
Acceleration	0.96	< 0.0001	0.98	< 0.0001	0.97	< 0.0001	0.98	< 0.0001
Energy	0.94	< 0.0001	0.96	< 0.0001	0.95	< 0.0001	0.97	< 0.0001
Position Std	0.88	< 0.0005	0.92	< 0.0001	0.94	< 0.0001	0.93	< 0.0001
Mean Force	0.21	> 0.05	0.29	> 0.05	0.13	> 0.05	0.25	> 0.05
Max Power	0.86	< 0.001	0.94	< 0.0001	0.90	< 0.0005	0.90	< 0.0005
Freq. Max Pow.	0.95	< 0.0001	0.94	< 0.0001	0.97	< 0.0001	0.97	< 0.0001
FA1 Power	0.94	< 0.0001	0.97	< 0.0001	0.97	< 0.0001	0.95	< 0.0001
FA2 Power	0.90	< 0.0005	0.93	< 0.0001	0.94	< 0.0001	0.92	< 0.0001
Total Power	0.95	< 0.0001	0.97	< 0.0001	0.97	< 0.0001	0.95	< 0.0001

Table 5.3: Correlation coefficients for various physical property $\Phi(I)$'s when compared to the roughness $\Psi(I)$ for dithered conical textures. Outliers have been removed from maglev and subject data.

Table 5.3 shows the correlation coefficients between $\Phi(I)$ and $\Psi(I)$ for a number of z -axis physical properties. The calculation of these parameters is described in Section 3.4.

The mean position and force $\Phi(I)$'s show very little correlation with the psychophysical function. This lack of correlation is also found for sinusoidal and trapezoidal gratings and is not unexpected since these properties relate more to subjects' exploratory procedures than to probe-texture interactions.

The remainder of the properties are all strongly correlated with the psychophysical function for all probe sizes. Velocity and acceleration in the z axis are both highly correlated to $\Psi(I)$ as is the kinetic energy and the standard deviation of z -axis position. All of these terms derive from changes in the position of the manipulandum.

The physical function for mean absolute z -axis velocity can be seen in Figure 5.9 as a set of heavy lines while the psychophysical function is shown as a set of light lines. The physical function has been normalized to the psychophysical function for display purposes and the functions are

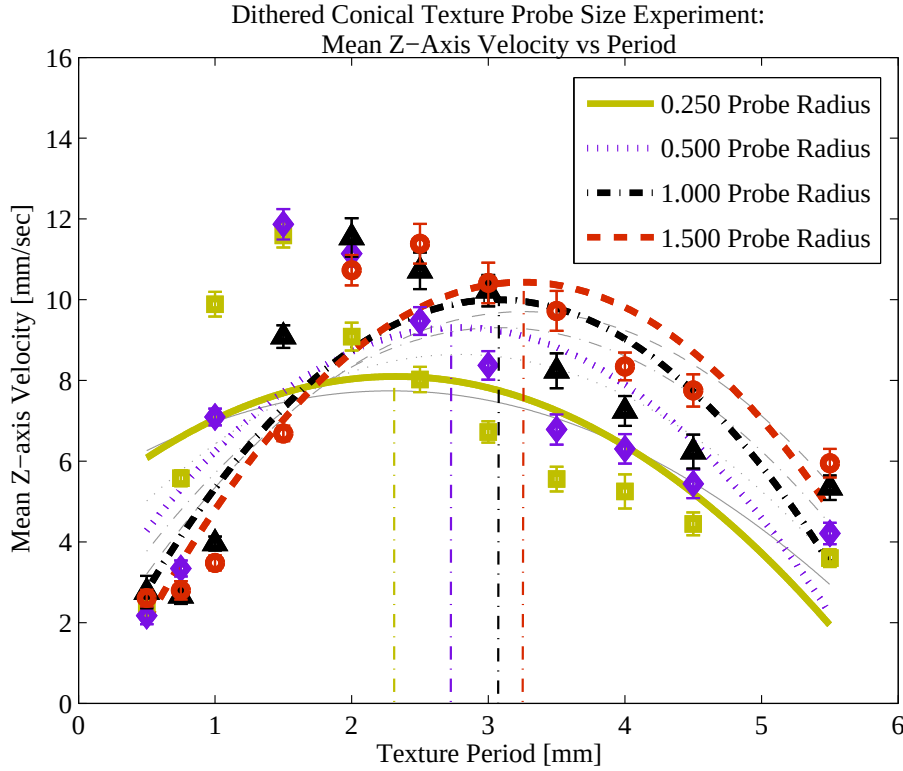


Figure 5.9: Dithered conical texture probe size experiment mean z -axis velocity versus texture period for four different probe sizes. Light lines indicate the roughness estimates for the same probe sizes and texture periods.

displayed on standard plot. The close fit between the two functions is readily apparent and the DPs and curvature are nearly identical (Table 5.4). Clearly, motion induced by probe-texture geometry is being perceived as roughness.

The power properties are all measures of the power in the z -axis force signal, determined from the integral of the PSD (see Section 3.4.4). Of these properties, the best correlation for all probe sizes appears to be with the PSD's total power from 5-500 Hz but all measures are well correlated. $\Phi(I)$ for total power in the z -axis force signal is shown along with $\Psi(I)$ in Figure 5.10. The DPs and curvature for each function are shown in Table 5.6. Once again, a close fit between the two functions can be seen.

Since most of the physical properties examined correlate strongly with the psychophysical function, it is impossible to determine, based on these results, which is the most salient with respect to roughness perception. It is clear that probe-texture geometry affects the motion of the manipulum. The resulting changes in position and power in the force signal are inter-related and are

	Roughness $\Psi(I)$		Z -axis Velocity $\Phi(I)$	
Probe Rad. [mm]	2nd Ord. Curv.	2nd Ord. Max. [mm]	2nd Ord. Curv.	2nd Ord. Max [mm]
0.25	-0.69	2.29	-0.61	2.32
0.50	-0.97	2.79	-0.96	2.79
1.00	-1.14	3.08	-1.10	3.06
1.50	-1.09	3.26	-1.11	3.25

Table 5.4: The curvature and element spacing at which the maximum occurs for unlogged second order fits to the dithered conical texture $\Psi(I)$ as well as the curvature and maxima location for similar 2nd order fits to the mean z -axis velocity $\Phi(I)$. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Roughness Curvature	3/92	3.36	< 0.05
Roughness 2nd Order Max.	3/92	27.42	< 0.0001
Velocity Curvature	3/92	26.28	< 0.0001
Velocity 2nd Order Max.	3/92	193.20	< 0.0001
Total power Curvature	3/92	5.36	< 0.005
Total Power 2nd Order Max.	3/92	1.15	> 0.05

Table 5.5: 1-way ANOVA results showing significance of probe size effects on curvature and maxima of an unlogged 2nd order fit to the z -axis velocity and total PSD power $\Phi(I)$'s as well as the roughness psychophysical function $\Psi(I)$.

perceived as roughness. Based on the sinusoidal grating experiment, which uses a much larger number of element spacings and thus provides a better measure of correlation, the total power in the force signal is the most salient of these factors (Section 3.4.4). Since the dithered cone experiment shows strong correlation between total power in the force signal and roughness, it does not contradict the previous findings and provides additional support for this hypothesis.

Correlation between the power in the FA1 and FA2 bandwidths and $\Psi(I)$ is strong for both factors. While the FA1 bandwidth (5-50 Hz) is the more strongly correlated of the two, the FA2 bandwidth (50-500 Hz) is not far behind. In both the sinusoidal and trapezoidal grating experiments the difference in correlation was larger. The sinusoidal grating experiment, in particular, showed a much larger correlation between z -axis force signal power in the lower frequencies, with a 20 Hz

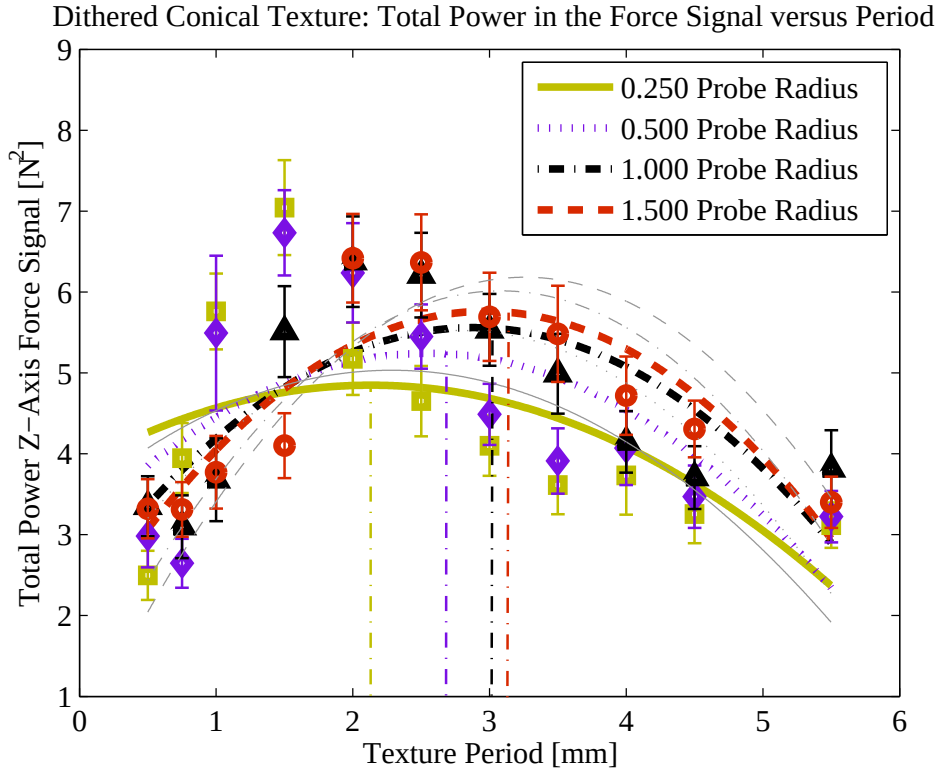


Figure 5.10: Second order fit to the total power in the z -axis force signal versus plotted against texture period for four probe sizes. Vertical lines indicate the location of the fit maxima and thin gray lines indicate subject roughness perception normalized to respective total power curves.

window centered at approximately 25 Hz correlating with roughness at the 0.90 level. The similar correlations of FA1 and FA2 bandwidths with roughness in this experiment likely reflect the small data set used to determine the correlation coefficients.

5.6 JND for Roughness with Dithered Conical Textures

The ability to discriminate between two real textures based on factors such as sandpaper grit number and sinusoid amplitude has previously been determined [53, 67]. The ability to discriminate between virtual textures based on element spacing, however, has not been examined. One argument made against performing such virtual texture discrimination experiments is that they are likely to depend on device performance. If a haptic device is unable to render texture sufficiently well, the discrimination threshold measured is likely to be related to device characteristics rather than to a subject's perceptual abilities.

Probe Rad. [mm]	Roughness $\Psi(I)$		Total Power of Force PSD $\Phi(I)$	
	2nd Ord. Curv.	2nd Ord. Max. [mm]	2nd Ord. Curv.	2nd Ord. Max [mm]
0.25	-0.69	2.29	-0.22	2.13
0.50	-0.97	2.79	-0.33	2.55
1.00	-1.14	3.08	-0.39	2.88
1.50	-1.09	3.26	-0.44	2.97

Table 5.6: The curvature and element spacing at which the maximum occurs for unlogged second order fits to the dithered conical texture $\Psi(I)$ as well as the curvature and maxima location for similar 2nd order fits to the total z -axis PSD power $\Phi(I)$. Results are shown for four probe sizes.

This is unfortunate since a haptic device offers a platform which can quickly and easily render textures with different qualities, expediting JND experiments and allowing careful control of the texture parameter settings involved.

The preceding experiments have demonstrated the high fidelity with which the psychophysical function for virtual roughness perception matches that found by other researchers for real roughness perception. This holds true particularly when the geometry of the real world probe-texture interaction is modeled in the virtual world. Since roughness perception appears to be nearly equivalent in real and virtual environments, threshold experiments for roughness which utilize the CSA and the MLHD should be valid for comparison with real world texture.

A variant of Kaernbach’s unforced weighted up-down JND staircase technique [60, 84] provides a way to take advantage of the unique capabilities of virtual texture JND determination (see Section 1.2.1). This technique presents users with two textures having different element spacings and asks subjects to guess which texture is rougher. One of the two texture spacings is held constant throughout a JND determination trial while the other spacing is changed each time a subject completes a guess. These spacings are called the base texture spacing (BTS) and comparison texture spacing (CTS) respectively.

Kaernbach’s technique assumes that the spacing stimuli are monotonically related to perceived roughness intensity. Based on this assumption, a subject answer that the larger element spacing is rougher is considered correct, while all other answers, including the “Don’t Know” option are considered wrong. A correct answer decreases the spacing difference between the BTS and CTS, while an incorrect or unsure answer yields an increase in the difference (see Sec. 1.2.1 and Sec. 2.4).

The size of the spacing difference varies according to the number of correct and incorrect guesses a subject makes in a trial (see Sec. 2.4).

The determination of JND is carried out for a range of base texture spacings (BTS) unique to each probe size. The criteria for BTS selection are described in Section 2.4. It is important to select BTSs that are smaller than the DPs of the probe size being studied. This prevents runaway JNDs. The runaway condition (see Section 2.4), in which the threshold grows larger rather than smaller as a subject proceeds through the experiment, results from the inverted “U”-shape of the psychophysical function for roughness. The JND determination assumes that larger element spacings produce rougher texture. This is clearly not the case when subjects have passed the point of maximum roughness on $\Psi(I)$. Thus, if the BTS is chosen too close to the DP, there is a chance subjects will move the wrong direction along $\Psi(I)$, increasing, rather than decreasing the determined JND threshold as the experiment progresses.

Klatzky *et al.*’s real dithered texture DPs are used as a guide to set the upper bounds on BTS for probe radii of 0.25, 0.5, and 1.0 mm. These upper bounds (1.0, 1.1 and 1.5 mm) are far enough below the DP for their respective probe sizes to prevent runaway JNDs if a subject makes an incorrect first guess. A universal lower bound for BTS of 0.5 mm is chosen to stay well within the MLHD’s resolution capabilities. Between upper and lower bounds the element spacing range is divided into 5 equidistant BTSs which can be seen in Table 5.7.

The experiment is divided into 3 blocks, each block representing a single probe radius crossed with all BTSs for that experiment. The ordering of blocks presented to subjects is counterbalanced across subjects. Fifteen JNDs are determined by each subject during the course of an approximately one hour experiment.

The just noticeable difference in element spacing, perceived as a change in the roughness of a surface, was determined using 12 subjects. The subjects were self-selected from a pool of psychology students who received course credit for the study, or they were paid student volunteers. All subjects (3 female, 9 male) were right-handed by self-report.

In spite of the careful choice of BTS designed to prevent runaway JNDs, these events still occur. In particular, they are noticeable for the largest BTS and the smallest probe size. Seven runaway JNDs were found for the 1.00 mm BTS with the 0.25 mm radius probe. One runaway trial was found for the 1.50 mm BTS and the 1.0 mm radius probe. All other JND determinations had no runaways. Runaways are detected as trials in which the last seven guesses were all incorrect, indicating that

Probe Radius [mm]	Base Texture Spacing [mm]				
	BT1	BT2	BT3	BT4	BT5
0.25	0.50	0.625	0.75	0.875	1.00
0.50	0.50	0.65	0.80	0.95	1.10
1.00	0.50	0.75	1.00	1.25	1.50

Table 5.7: Probe radius and base texture spacing used for dithered conical texture JND experiments.

subjects are consistently labeling textures with larger spacings as smoother than those with smaller spacings.

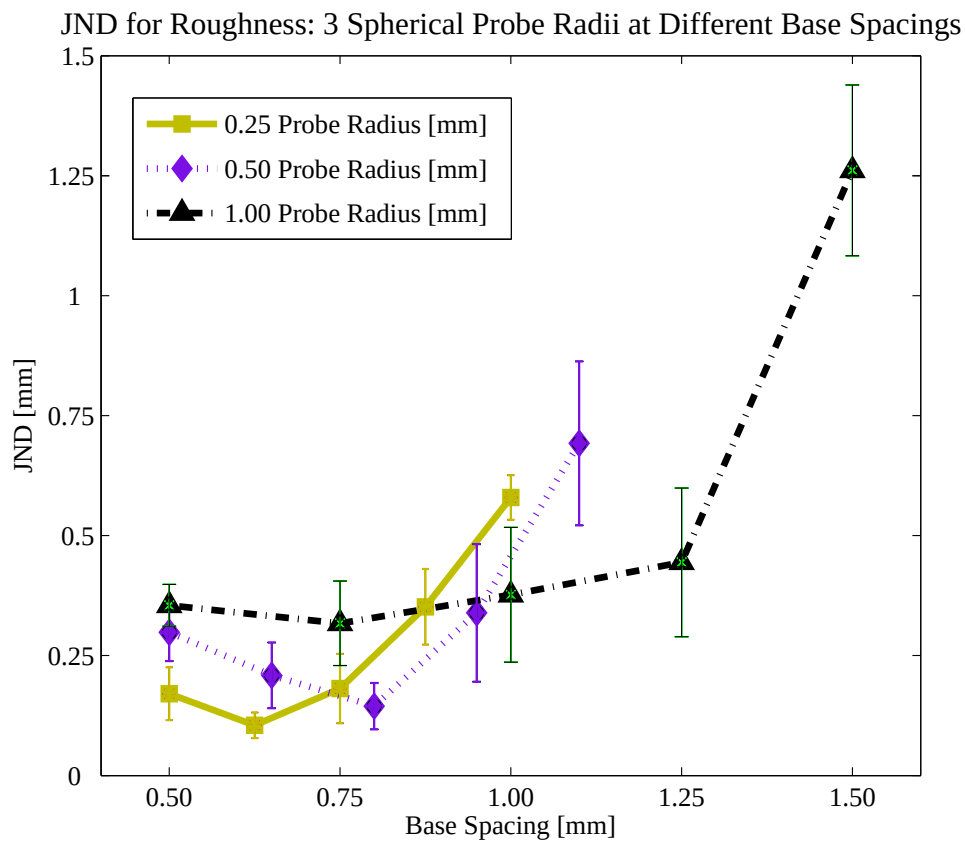


Figure 5.11: Threshold of the change in spacing that results in a JND in roughness for three different probe radii measured at a variety of base spacings.

JNDs for each probe size and BTS are determined by taking the mean JND over all subjects, excluding those trials found to be runaways. The JND for each BTS and probe size may be seen in Table 5.7. JND varies both with base spacing and with the size of the probe used to explore

the surface. Figure 5.11 shows that, for the range of base spacings shown, JNDs initially decline slightly and then increase dramatically. It can also be seen that, initially, the JNDs for all probe sizes are effectively identical but that as base spacing increases, larger probe sizes result in significantly larger JNDs. Several factors may explain this finding.

Probe Radius [mm]	Base Texture JND [mm]				
	BT1	BT2	BT3	BT4	BT5
0.25	0.170	0.105	0.181	0.352	0.579
0.50	0.298	0.209	0.145	0.339	0.692
1.00	0.355	0.317	0.377	0.444	1.261

Table 5.8: Just noticeable differences for probe radius–base texture pairings.

Since the largest BTSs are closest to the DPs for their respective probe sizes, it appears that there is an inverse correlation between higher subjective roughness intensity and the ability to discriminate between textures. It is possible that large motion and force variability saturates neural receptors when subjects are experiencing maximum roughness near the DP. The changing slope of the approximately quadratic $\Psi(I)$ implies that changes in roughness with respect to changes in element spacing are rapid when measured far from the DP but slow as the DP is approached. This is reflected in JNDs which are smallest for the smaller BTSs which are far from the point of maximal roughness at DP.

The variability in JND as measured by the error (see Fig. 5.11) is also lower for smaller BTSs which are further from the DP. This demonstrates that JNDs are more consistent at element spacings where roughness is low but changing quickly.

It should be noted that, while runaway JNDs were eliminated to the greatest extent possible, the exclusion criteria (seven incorrect answers in a row) can fail if subjects make “accidental” correct guesses occasionally. Since runaways are likely to be more common with larger BTS, this may result in overestimation of, and larger variability in, the JNDs for large BTS.

Probe size is not found to have a significant effect on JND in a 1-way ANOVA, although, as seen in Figure 5.12, there appears to be a trend of increasing JND with increasing probe size. Figure 5.12 shows JNDs for BTSs which are approximately the same distance from the DP for their probe size. If the curvature of $\Psi(I)$ were identical across probe sizes, then the JNDs should be nearly identical. Absolute curvature of $\Psi(I)$ actually decreases significantly with increasing probe size, as seen in

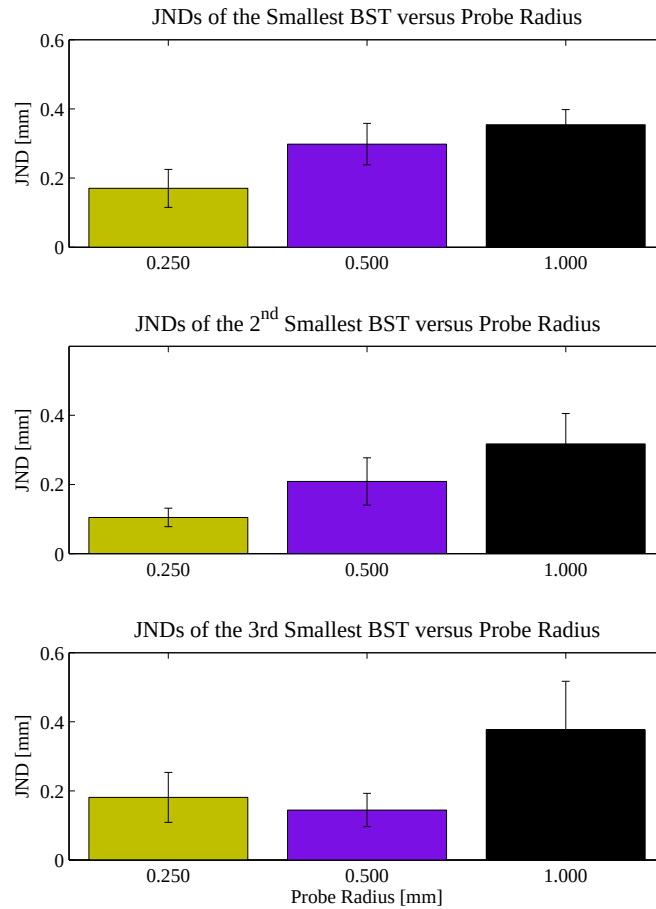


Figure 5.12: The relation of JND to probe size for similar base texture spacings (by quintile).

Section 5.4. For the same operating point on different probes' psychophysical functions, a smaller probe should be more sensitive to changes in spacings than a larger one. This may explain the trend for increasing JND with increasing probe size.

Clearly, JNDs for the smallest BTS are the most accurate, and, for the MLHD and dithered conical textures produced with the CSA, range from 0.105 to 0.317 mm. While these values are well above the position resolution of the MLHD, it is possible that they are somehow related to device capabilities such as force resolution, or some shortcoming in the CSA. Comparison with real JNDs for dithered conical textures would be useful. Study of the effect of changes in operating properties such as surface compliance, to be addressed in Chapter 7, may also reveal potential pitfalls of the virtual JND approach.

5.7 Conclusions

The dithered conical texture experiment is designed to be similar to real dithered conical texture experiments conducted by other researchers. The goal is to demonstrate that, with careful simulation of the geometry of probe-texture interaction, virtual roughness perception is equivalent to real roughness perception. Previous studies with virtual sinusoidal texture had demonstrated some concerns that this might not be possible [68, 91, 107].

The preceding two experiments with sinusoidal and trapezoidal textures clearly demonstrate that, when applying these two models, the psychophysical function for roughness, $\Psi(I)$, does not assume the inverted “U”-shaped form associated with real dithered conical textures [20, 63, 65, 66, 74, 76, 79]. This suggests that the probe-texture geometry is responsible for $\Psi(I)$ ’s shape rather than some fundamental difference between virtual and real texture perception.

The dithered conical texture experiments confirmed that probe-texture geometry is, indeed, the defining factor in roughness perception. By modeling the interaction between a realistically-shaped virtual probe and virtual dithered texture geometry, a psychophysical function shape is found that is nearly identical to that found with real textures. The approximately quadratic shapes of the virtual functions, along with their maxima and curvature, closely resemble real functions for comparable probe sizes. The location of the element spacing at which drop points occur with virtual probes of different sizes, is nearly identical to that found with real probes and textures and is predicted by Klatzky *et al.*’s geometric model [66].

The underestimation of real DPs by the geometric model is likely due to the model’s quasistatic assumptions. In Section 4.4, the geometric model was extended by taking probe velocity into account. Application of this extended model results in predicted DPs for dithered conical textures which are very close to experimentally determined results.

In the investigation of sinusoidal gratings in Chapter 3, the physical property characterized by subjects as roughness was determined to be the total power in the z -axis force signal. The high degree of correlation between this physical property and the psychophysical function for roughness led to this conclusion. For dithered conical textures, total power, along with most of the physical properties examined, had high levels of correlation with $\Psi(I)$, and thus, the property most responsible for roughness could not be determined from this experiment alone. The high correlation of all properties is likely due to their inter-related nature and the small number of data points in the correlated functions. Total power was one of the highest correlated functions in this experiment.

This fact, taken together with the trapezoidal grating study of Chapter 4 and the more reliable sinusoidal texture experimental findings of Chapter 3, indicate that total power is indeed responsible for roughness.

The relative contributions of the FA1 and FA2 neural receptors to roughness perception could not be determined in this experiment since the power in both of their bandwidths are highly correlated with roughness. The FA1's slightly higher correlation is not significant enough to draw any conclusions.

The minimum JND for roughness, based on changes in element spacing, was determined to be between 0.105 and 0.317 mm, for spherical probes ranging from 0.25 to 1.0 mm in radius. The effect of probe size on JND was not found to be significant although a trend of increasing JND with increasing probe size was seen. JND tended to increase with increasing BTS, a phenomenon which is likely related to higher subjective sensitivity to roughness when roughness intensity is small. It is possible that at high intensities neural receptors become saturated, although other mechanisms, such as the nature of receptor response filtering characteristics, may play a role.

Having determined that the CSA model of probe-texture geometric interaction produces psychophysical functions for roughness which accurately reflect those found with real textures, the effects of probe shape, probe compliance and surface friction on roughness perception will be investigated in the following chapters.

Chapter 6

Dithered Conical Textures and Probe Shape

6.1 Introduction

This thesis has demonstrated that an infinitely small point-probe crossing sinusoidal gratings generates a different perception of roughness than does a spherical probe crossing dithered conical textures. It has also demonstrated that the size of the spherical probe alters roughness perception in ways predicted by a geometric model originally developed for real textures [66]. Clearly, real and virtual probe-texture geometries affect the dynamics of probe-texture interaction in similar ways.

Further information on how probe geometry affects texture perception may be discovered if the basic probe shape is changed. Changes to the probe's shape require a new set of equations to describe the altered constraint surface it is expected to follow. A new set of equations will also be necessary to predict the drop point (DP), defining the element spacing at which the probe is maximally penetrating the texture. The geometric model for roughness indicates that the DP should be the point of maximum subjective roughness. If the model holds, the DPs predicted by the new equations should be confirmed by experimental results.

Changing the shape of the probe to a cone should not change the physical property which characterizes roughness. While the resulting change in the constraint surface geometry may modify the probe's dynamic behavior, the frequency of its vibrations, or the size of the forces applied to it, the association between the salient physical property and roughness should not be fundamentally altered. Correlation between roughness magnitude and the total power in the z -axis force signal, the property most likely perceived as roughness based on experiments so far, should remain high, even though the probe shape is no longer spherical.

The JND for roughness may be altered by probe shape, since the roughness detection threshold is related to the slope of the psychophysical function for roughness, a factor which may be affected by changes to constraint surface geometry. The exact nature of the relationship between the form of the psychophysical function and probe geometry has not been determined. It seems likely that it is related to the smoothness of the path the probe follows over a surface.

It has been shown that for spherical probes, the larger the probe, the smaller the absolute curvature of $\Psi(I)$ (Section 5.4). Large spherical probes move along paths which have larger arcs. They therefore experience smaller changes in vertical position and force than small probes, for equal horizontal displacements. It is thus possible that the smoother path results in smaller curvatures of $\Psi(I)$, lowering sensitivity to changes in element spacing.

Similar path smoothing occurs as the size of conical probes increases. The $\Psi(I)$ s of large conical probes should therefore exhibit lower absolute curvature than those of small probes. Additionally, discontinuities in the path of conical probes which result from abrupt changes in path angle (see Section 6.2 below) may generate signal noise. This noise may further reduce subjects' ability to detect changes in element spacing. Conical probes might be expected, therefore, to have smaller absolute roughness function curvatures than spherical probes of the same radius.

6.2 The Constraint Surface Algorithm for Cone-shaped Probes

The constraint surface algorithm (CSA) for dithered conical textures can be most easily applied to probes that are radially symmetric about the vertical axis. If a radially symmetric probe is constrained to keep its vertical center line parallel to the z axis at all times, contact symmetry with texture elements is also preserved. Symmetry allows the parametric equations, which govern the cone's desired height above the z axis, to be calculated based on its distance from the nearest texture element. If two texture elements are equidistant, their effects on the conical probe's height are identical based on symmetry. This reduces algorithm complexity.

In the following experiment an inverted right circular cone (*i.e* having its base as its highest point) is used as a virtual probe to explore the dithered truncated cone textures studied in Chapter 5. The haptic interaction point (HIP) is located at the center of the cone's base. The probe will have a base radius, R_{probe} and a height, h_{probe} .

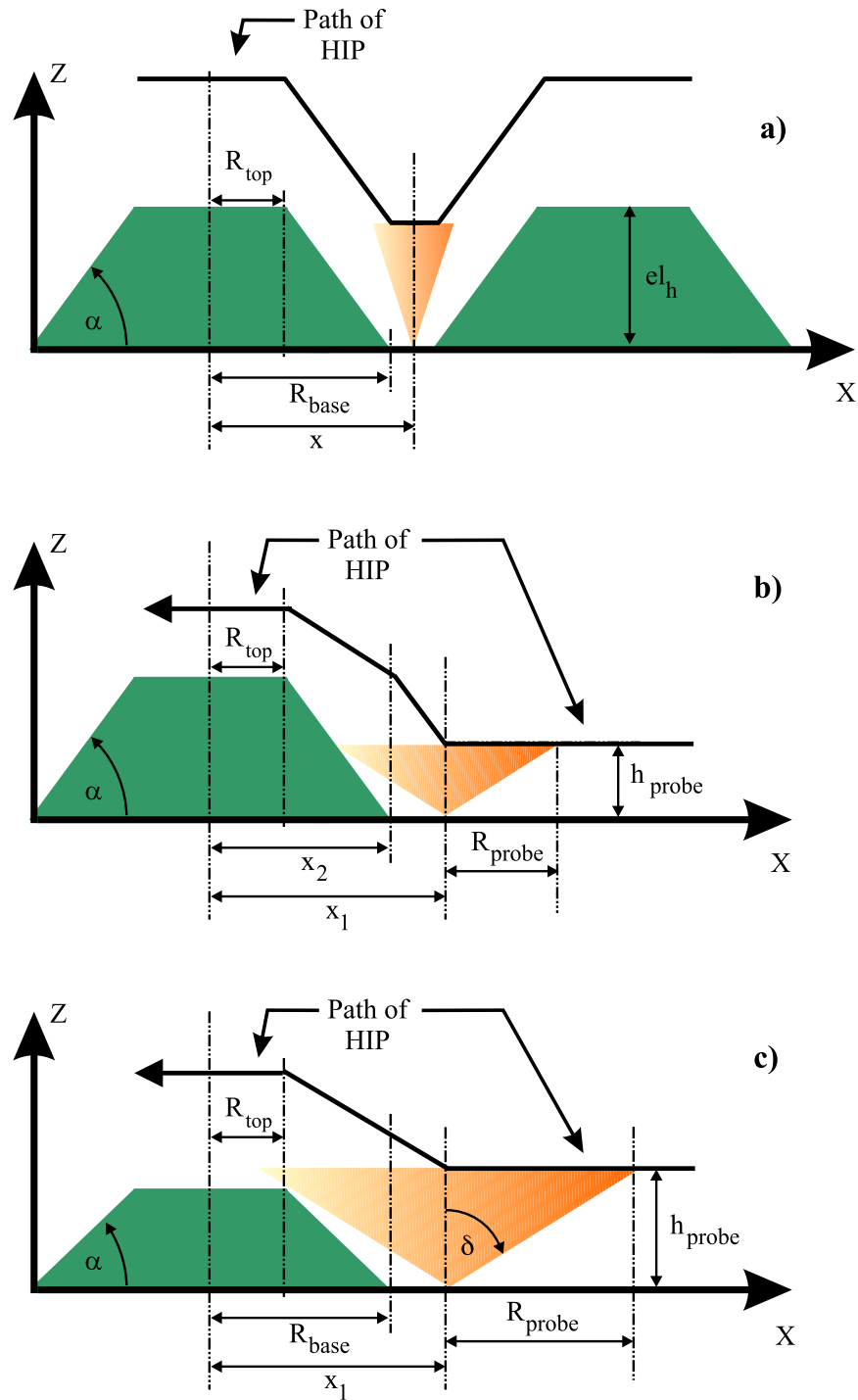


Figure 6.1: Constraint surface algorithm for probes with conical shape. Three conditions exist which depend on the relationship between probe height, h_{probe} , the probe's pitch angle, δ and the texture element angle, α : a) $90^\circ - \delta \geq \alpha$, b) $90^\circ - \delta < \alpha$ and $h_{probe} < el_h$, and c) $90^\circ - \delta < \alpha$ and $h_{probe} \geq el_h$.

Three possible constraint surfaces exist for cone-shaped probes. The path of the HIP, as it crosses these surfaces is shown in Figure 6.1. As the HIP approaches and makes contact with a texture element, the constraint surface which it will follow depends on the relationship between the angle of the element's side wall, α , and the pitch angle of the cone, δ . δ is defined as the 1/2 of the cone's aperture angle, or, alternatively, as the angle between the cone's outside surface and the vertical line from its apex to the center of its base (see Fig. 6.1).

The first of the three possible constraint surfaces may be seen in Figure 6.1a. In this case, the probe angle δ , makes the probe's surface steeper than the contacted element's side wall ($90^\circ - \delta \geq \alpha$). This causes the HIP to move parallel to the side-wall of the texture element when the cone apex comes into contact with it. Since the cone angle is steeper than the slope of the texture element, the base of the cone can never contact the element.

The absolute distance of the HIP from the center of the nearest texture element is defined as d . d will decrease in magnitude as the probe approaches the element from any direction. Knowing the value of d , the z -axis position of the HIP for this case, z_{des} , may be determined as follows:

$$d \geq R_{base} : z_{des} = h_p, \quad (6.1)$$

$$R_{top} \leq d < R_{base} : z_{des} = h_p + (R_{base} - d) \tan \alpha, \quad (6.2)$$

$$0 \leq d < R_{top} : z_{des} = h_{probe} + el_h. \quad (6.3)$$

When a cone-shaped probe has a narrow aperture like this, it will always fully penetrate between elements and thus its DP can be calculated as $DP_{cone} = 2R_{base}$. Effectively, any probe of this type will act as if it were an infinitely small point probe, following the texture profile exactly, but elevated above it.

The path of the HIP over a second possible constraint surface is shown in Figure 6.1b. Here, the cone angle is less steep than the slope of the element side wall ($90^\circ - \delta < \alpha$), but the height of the probe is less than that of the texture elements ($h_{probe} < el_h$). In this situation, a probe, approaching an element, first makes contact between the edge of the probe base and the element sidewall when the HIP position d , reaches a distance, d_1 , from the center of the texture element. d_1 can be determined as follows:

$$d_1 = R_{top} + R_{probe} + (el_h - h_{probe}) \cot \alpha, \quad (6.4)$$

Prior to reaching d_1 , the HIP is constrained to a z -axis position equivalent to the height of the probe:

$$d > d_1 : z_{des} = h_{probe}. \quad (6.5)$$

Once d_1 is reached, the probe, constrained to only translational motion and unable to rotate, slides along the side of the element to position d_2 , where $d_2 = R_{top} + R_{probe}$:

$$d_2 \leq d < d_1 : z_{des} = (R_{probe} + R_{base} - d) \tan \alpha. \quad (6.6)$$

Throughout this motion the probe maintains its vertical position.

When the HIP reaches d_2 , the top edge of the texture element is now in contact with the lateral surface of the probe and the HIP will move at a new angle until it is a distance R_{top} from the element center:

$$R_{top} \leq d < d_2 : z_{des} = (R_{probe} + R_{top} - d) \cot \delta + el_h. \quad (6.7)$$

Once the HIP has reached the lip of the element at $d = R_{top}$, it remains a constant distance above the x axis until it reaches the element center, at $d = 0$:

$$0 \leq d < R_{top} : z_{des} = h_{probe} + el_h. \quad (6.8)$$

In this case of a shallow-sloped probe which is shorter than the texture elements, the texture spacing at which the probe achieves maximum penetration depth, DP_{cone} , can be found as:

$$DP_{cone} = 2(R_{top} + R_{probe} + \frac{(el_h - h_{probe})(R_{base} - R_{top})}{el_h}), \quad (6.9)$$

Finally, a third constraint surface for cone-shaped probes exists, although it is not used in this experiment. In this case, the probe's angle, δ , is less steep than the texture elements' side walls ($90^\circ < \alpha$), but probe height is greater than that of the elements ($h_{probe} > el_h$). The path of the HIP over such a surface can be seen in Figure 6.1c. In this case, the z -axis height of the HIP is constant until $d = d_1$, when the lip of the texture element contacts the lateral surface of the cone:

$$d \geq d_1 : z_{des} = h_{probe}. \quad (6.10)$$

After d_1 is reached, and until the HIP reaches the lip of the element where $d = R_{top}$, the z -axis position of the HIP is found as:

$$R_{top} \leq d < d_1 : z_{des} = (R_{top} + R_{probe} - d)\cot\delta + el_h. \quad (6.11)$$

Finally, when the HIP moves from the lip towards the center of the element its height is found as

$$0 \leq d < R_{top} : z_{des} = el_h + h_{probe}. \quad (6.12)$$

In this case, the drop point is determined to be

$$DP_{cone} = 2(R_{top} + \frac{R_{probe}el_h}{h_{probe}}). \quad (6.13)$$

In the experiment which follows, the height of the cone-shaped probe is constant and less than the height of the texture elements. Only the first two cases are therefore represented. This makes the number of probe conditions in the experiment manageable.

The probe parameter which is to be experimentally manipulated is the base radius (R_{probe}), while probe height is held constant. This changes the aperture of the cone and thus, as R_{probe} increases, δ will go from less than $90^\circ - \alpha$ to greater than $90^\circ - \alpha$.

The probe radii selected for the experiment are 0.0625, 0.25, 0.5, 1.0 and 1.5 mm. These radii result in probe angles of 14° , 45° , 63° , 76° and 81° respectively. A truncated cone is used as the texture element, identical to the element used in Chapter 5. It has a height of 0.42 mm and a side angle, α , of 53° . The two smallest probe radii in the experiment therefore use a constraint surface that parallels the texture surface exactly. It is thus predicted that there should be no significant difference between the roughness profiles for the smallest two probes.

The constraint surface for the larger 3 probes is not very different from that of a spherical probe. The primary difference is that a cone-shaped probe surface has sharper discontinuities than does a spherical probe surface. As described above (Section 6.1) this may increase curvature and decrease JND.

6.3 Roughness Magnitude Estimation Experimental Design

The cone-shaped probe experiment used the same truncated cone texture elements previously described in Chapter 5, Section 5.3 ($el_h = 0.42$ mm, $R_{top} = 0.23$ mm, $R_{base} = 0.52$ mm, $\alpha = 53^\circ$). The texture element locations were dithered with zero-mean white noise as previously described in Section 5.3 with a range of mean spacings from 0.25-5.5mm. The complete range of spacings may

be found in Appendix B, Section B.1.4. The cone-shaped probes had a height of 0.25 mm and base radii of 0.0625, 0.25, 0.5, 1.0 and 1.5 mm. The height and base radii were chosen to ensure that a wide range of cone angles could be generated just by changing the base radius parameter. The height placed the HIP at 0.25 mm above a flat surface, approximately where it would be if a 0.25 mm radius spherical probe were in use.

Proportional contact gains were set at 10 N/mm and 25 Nm/radians while derivative gains were 0.04 N/mm/s and 0.5Nm/radian/second for translation and rotation respectively. These gains were the same as those used for all other thesis experiments except those explicitly involving compliance (Chapter 7) and provide a subjectively stiff surface without significant instability.

Twenty-five subjects took part in the cone-shaped probe magnitude estimation experiments including 12 female and 13 male subjects. Only 1 subject was left-handed by self-report but performed the experiment with the non-dominant hand. All subjects were drawn from the Carnegie Mellon Psychology Department's student experiment research pool and received course credit for participation.

Subjects were seated approximately 500 mm from a graphical display used to enter the roughness estimates, with the MLHD on their right-hand side. Texture was only displayed haptically. White noise, played through headphones ensured that audio cues were not available to help subjects discriminate between textures.

Subjects were notified that they would encounter the textures as a series of trials. Trials were presented in two blocks: a demonstration block and an experimental block. The demonstration block consisted of 25 trials, in which five texture spacings, spanning the range of 0.25-5.5 mm, and all five cone-shaped probe radii were displayed in random order. After the demonstration block, the actual magnitude estimation began. Subjects entered a numeric value using a computer keyboard and were informed of their progress by a reported trial number but otherwise received no other feedback on performance. Subjects were not instructed how to feel the texture and were given no restrictions on time. Although experiments were slated to run for one hour, most subjects finished in much shorter time frames.

Subjects were told that they could assign roughness estimates to any positive range of numbers but that larger numbers were to reflect larger values of roughness and smaller numbers were to represent smaller values of roughness. They were specifically asked not to use 0 or negative numbers.

Recorded data consist of subject roughness magnitude estimates as well as 1000 Hz continuous sampling of the HIP position and commanded z -axis forces.

6.4 Roughness Perception and the Effects of Probe Shape

In previous experiments in this thesis, the psychophysical function for roughness was found to assume a shape which was dependent on the geometry of the texture and whose parameters were influenced by probe shape. For sinusoidal gratings explored with a point-probe, the shape of $\Psi(I)$ was roughly linear, with a negative slope (Chapter 3). For trapezoidal gratings, $\Psi(I)$ assumed the shape of a logistic function whose maximum point was determined by the size of the exploring spherical probe (Chapter 4). For dithered conical textures, $\Psi(I)$ was fit well by a quadratic, the maxima of which was also determined by the size of the spherical probe employed (Chapter 5).

In this experiment, the shape of the probe is conical while the texture geometry is the same set of dithered cones used in the preceding chapter. The smallest two probe sizes, as described above, both have δ 's that cause them to act as if they were point probes. The CSA for both generates the same surface. The smallest probes thus act as a control. First, they reproduce the results that would be found if an infinitely small point-probe crossed a dithered conical surface – the traditional approach to studying virtual texture. Second, since the 0.0625 and 0.25 mm probes both follow the same constraint surface, their psychophysical functions for roughness should be identical. Significant differences in function shape would imply high degrees of inter-subject variability for roughness perception and cast doubts on the reliability of virtual texture experiments. Fortunately, examining figure 6.6 it appears that, for the smallest two probe sizes, the psychophysical functions for roughness overlap to within the limits of error.

It is interesting to note that, for the 0.0625 and 0.25 mm radii conical probes, the magnitude estimation data are well fit by a quadratic curve, with R^2 values of 0.94 and 0.90 respectively. A third order fit to these functions shows only slight improvement (See Table A.24). Examining the data in Figure 6.2 and the second and third order fit equations of Table A.24, it is obvious that the second order fit gradually declines in quality as probe size increases, while a third order fit becomes more appropriate, especially for the larger conical probes.

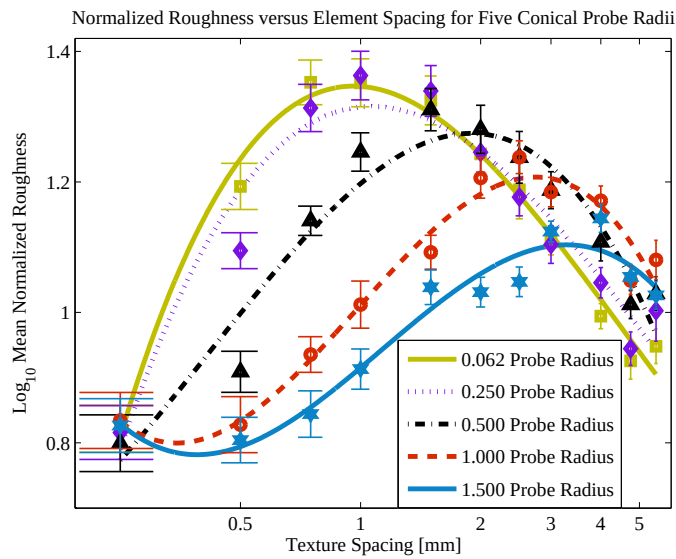
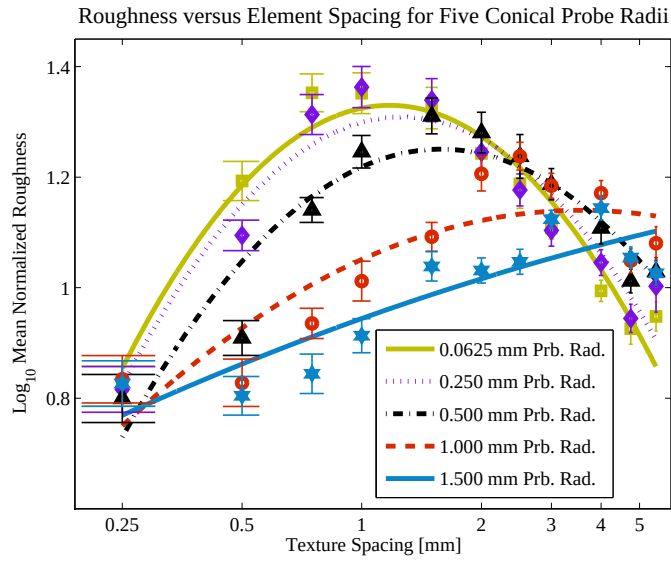


Figure 6.2: a.) Second order fit to mean normalized roughness estimates of dithered conical textures explored with conical probes of 0.0625 to 1.5 mm radius. Probe height was 0.25 mm b.) Third order fit to the same roughness estimate data.

The reason for this trend is related to the probe-texture geometry. At the smallest element spacing in this experiment (0.25 mm), the texture cones, which have a top radius, R_{top} , of 0.23 mm, overlap completely, presenting an entirely smooth surface to the subjects. All probe sizes, therefore, find the surface completely smooth. Figure 6.6a shows that the $\Psi(I)$ s for all probe sizes converge at the smallest element spacing. A completely smooth surface is therefore rated by subjects as approximately 0.8 on the normalized log scale used in the figure.

At the next spacing of 0.5 mm, the texture cones still overlap but shallow gaps between them are now appearing. The smallest probes (essentially point-probes as described above), are able to penetrate to the bottom of these gaps, while larger probes will penetrate only slightly. The change in subjective roughness from completely smooth to slightly rough must require some minimum threshold of change in penetration depth. This threshold is achieved at larger spacings by larger probes. Thus large probes have $\Psi(I)$'s which begin with an initial "flat" region and then develop an inverted "U"-shaped curve. Small probes show the inverted "U"-shaped curve earlier since, with the element spacings selected for this experiment, they surpass the hypothetical threshold almost immediately. The length of the initial "flat" region of $\Psi(I)$ should depend on the δ of the larger conical probes; the larger the δ , the longer the region. This can be clearly seen in Figure 6.6b, where the larger the probe radius, the longer and flatter the initial part of $\Psi(I)$.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.06	-1.05	1.04	1.18	0.96
0.25	-0.99	1.04	1.26	1.06
0.50	-0.81	1.68	1.58	1.90
1.00	-0.29	2.68	3.56	2.75
1.50	-0.06	3.68	176.32	3.29

Table 6.1: The maxima of the cone-shaped probe texture roughness functions based on 2nd and 3rd order curves in a log-log plot. Curvature of the 2nd order fit to roughness data and the predicted drop points for five sizes of cone-shaped probe.

This trend, in which small probes exhibit roughly quadratic, and large probes, roughly cubic, $\Psi(I)$ s is also seen with spherical probe shapes but is not as marked since the smallest spacing studied was 0.5 mm in that experiment. (See Section 5.4, Figure 5.4 for spherical probe fits and Table A.19 for R^2 values).

Factor	DOF	F	p-value
Curvature	3/84	18.02	< 0.0001
Curve Height	3/84	4.43	< 0.01
2nd Order Maxima	3/84	0.34	> 0.05
3rd Order Maxima	3/84	15.64	< 0.0001

Table 6.2: Significance of probe radius effects on roughness functions in the cone-shaped probe experiment, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to roughness estimates in a log-log plot. Only the largest four probes were analyzed.

The element spacing at which maximum roughness occurs (the DP) is found from the quadratic and cubic fits to the conical probe data (Table 6.1). The DP is seen to increase with increasing element spacing for both second and third order fits. The effect of probe radius on DP is significant for a third order fit but not for a second order fit, even when only the largest four probes are analyzed (Table 6.2).

The trend of increasing DP with probe size is in agreement with the geometric model for roughness which predicts that, the larger the probe, the larger the spacing at which maximum roughness will be found. The predicted DP for conical probes, based on the equations of Section 4.4, is fairly close to the experimentally determined DPs. In particular, the second order fits are close for the smallest two probe sizes, while the third order fits are best for the larger three sizes. For the second order maximum, the extremely large DP for the largest probe (176.32 mm) is a result of a very poor fit to the data.

The underestimation of the DP by the quasistatic geometric model, seen in Section 5.4, appears to be less significant for conical probes. Since the mean planar velocity over all subjects and trials, for conical probes was 33.4 mm/sec, the predictions of the geometric model revised for probe velocity need to be adjusted upwards by 0.31 mm (see Section 4.4, Equation 4.16). The velocity corrected geometric model, therefore, tends to slightly overestimate the determined DPs for conical probes. Whether this is due to statistical variation in determining subjective roughness or an underlying aspect of the conical probes is uncertain. Possibly the discontinuities in the constraint surface for conical probes generate a “noisier” force signal which makes subjective roughness determination more uncertain. If this is the case, the JND associated with conical probes should be larger than those seen with spherical ones.

The height of the point of maximum roughness is affected significantly by probe radius (Table 6.2) and declines as the size of the probe increases. This can be explained with reference to Figure 6.1b. When a conical probe is at its DP, its point is resting on the base surface and its edge is resting against an element. As it moves towards the element, it will move upwards at the element's side angle, α for a short (in the (x, y) plane) distance. This distance is related to cone height, which, in this experiment is constant. The second phase of motion will be upward at the angle δ , the probe's pitch angle. The distance of this second phase of motion is related to probe radius, which increases with δ and is generally much larger than the first phase. The slope of this second motion is also less than that of the first. Thus, for increasing conical probe size, the rate of change in the z -axis position is smaller, just as it is for spherical probes. If z -axis force variability is the physical property which characterizes roughness, then this more gradual change in motion and presumably force, explains the decrease in the height of $\Psi(I)$ as probe size increases. This also explains the significant decrease in curvature seen as probe size increases.

6.5 Probe Shape and the Physics of Roughness

Strong evidence is presented in Chapter 3 that the physical property characterizing roughness is the variability in the z -axis force signal, as determined by the total power in its PSD periodogram. This hypothesis is further supported by the finding that correlation between the physical function for force variability ($\Phi(I)$) and the psychophysical function for roughness ($\Psi(I)$) remains high for changes in texture and probe geometry. Experiments with trapezoidal and dithered conical textures both support this hypothesis.

Changing the probe from a point-probe to a sphere substantially alters the shape of $\Psi(I)$ but does not change its correlation with the $\Phi(I)$ for z -axis force variability. As seen in Section 6.4, changing the probe shape from a sphere to a cone, produces yet another change in the shape of $\Psi(I)$. If the $\Phi(I)$ for z -axis force variability continues to correlate with roughness in spite of this change, it provides further evidence that neither probe nor texture geometry affect which physical property characterizes roughness.

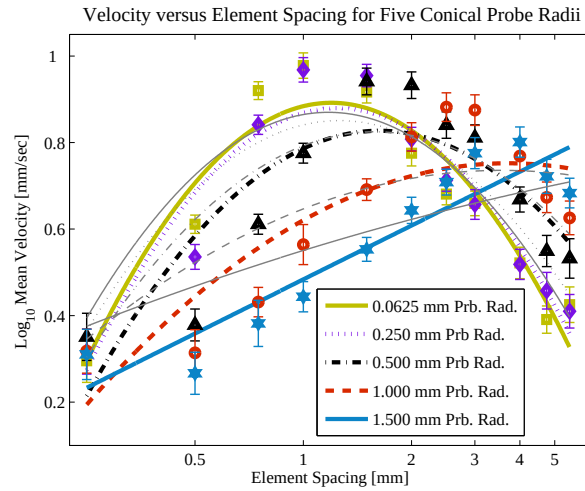
Table 6.3 shows the correlation coefficients between roughness and the same set of physical properties examined in previous chapters and defined in Section 3.4. Once again it can be seen that a significant number of the properties correlate well with roughness, including those derived from the position signal: z -axis velocity, acceleration and kinetic energy. The $\Phi(I)$ for velocity can be

	0.25 mm Probe		0.5 mm Probe		1.0 mm Probe		1.5 mm Probe	
Parameter	Corr. C.	p	Corr. C.	p	Corr. C.	p	Corr. C.	p
Mean Position	0.24	> 0.05	0.07	> 0.05	0.43	> 0.05	-0.04	> 0.05
Velocity	0.98	< 0.0001	0.97	< 0.0001	0.98	< 0.0001	0.97	< 0.0001
Acceleration	0.98	< 0.0001	0.96	< 0.0001	0.97	< 0.0001	0.95	< 0.0001
Energy	0.95	< 0.0001	0.92	< 0.0001	0.95	< 0.0001	0.95	< 0.0001
Position Std	0.69	< 0.05	0.73	< 0.05	0.62	< 0.05	0.79	< 0.005
Mean Force	0.69	< 0.05	0.82	< 0.005	0.64	< 0.05	0.57	> 0.05
Max Power	0.85	< 0.001	0.87	< 0.001	0.90	< 0.0005	0.63	< 0.05
Freq. Max Pow.	0.95	< 0.0001	0.91	< 0.0005	0.88	< 0.0005	0.91	< 0.0001
FA1 Power	0.96	< 0.0001	0.92	< 0.0001	0.96	< 0.0001	0.92	< 0.0001
FA2 Power	0.96	< 0.0001	0.93	< 0.0001	0.86	< 0.001	0.77	< 0.01
Total Power	0.96	< 0.0001	0.92	< 0.0001	0.96	< 0.0001	0.92	< 0.0001

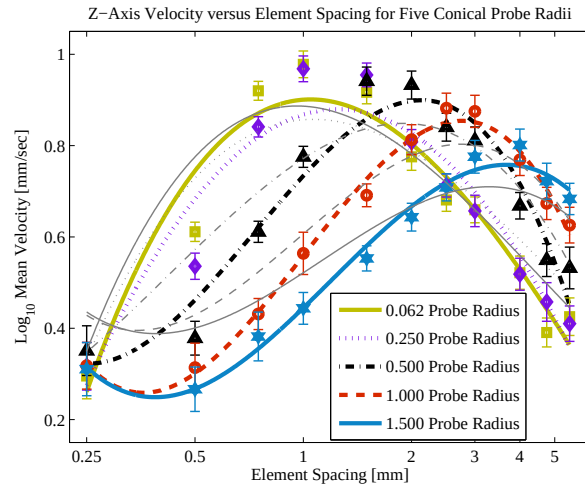
Table 6.3: Correlation coefficients for the physics function ($\Phi(I)$) of various physics properties when compared to the psychophysical function for roughness ($\Psi(I)$) for the largest four sizes of conical probe. Outliers have been removed from maglev and subject data.

seen in Figure 6.3, superimposed on the roughness $\Psi(I)$ with both second and third order fits to the data. The fits for velocity are good as quadratics for the smallest probe sizes but third order fits are better for the larger probes. The fit equations and R^2 values can be found in Appendix A, Table A.25.

From Figure 6.3, it can be seen that the maxima for both second and third order fits to velocity are well aligned with those of roughness and the trend of decreasing function height with increasing probe radius is also present. The mean absolute difference in third order maxima location between roughness and velocity is 0.17 mm. The effects of probe size on function height and the location of the DP is not significant, as determined by a 1-way ANOVA (see Table 6.5) using only the data from the largest four probe sizes. However, the curvature of the second order fits is significantly affected by probe radius, its absolute value declining as probe size increases. (Table 6.4). This decrease in absolute curvature likely reflects smaller changes in force generated by larger probes since they are following a constraint surface which has less extreme changes in z -axis geometry (see Section 6.3).



(a)



(b)

Figure 6.3: a.) Second order fit to mean z -axis velocity in a log-log plot for dithered conical textures explored with conical probes of 0.0625 to 1.5 mm radius. Probe height was 0.25 mm b.) Third order fit to the same data. Subject roughness estimates, normalized to velocity, are shown as thin gray lines.

Most measures of the power in the z -axis force signal correlate well with roughness for all probe sizes. This includes the total power and the power in both the FA1 (5-50 Hz) and FA2 (50-500 Hz) neuroreceptor bandwidths. The $\Phi(I)$ for total power can be seen in Figure 6.4 with both second and third order fits to the data. As previously seen for both roughness and velocity functions, a second

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.06	-1.29	1.04	1.20	1.05
0.25	-1.25	1.04	1.24	1.26
0.50	-0.93	1.68	1.63	2.14
1.00	-0.41	2.68	3.71	2.75
1.50	-0.00	3.68	>>100.0	3.63

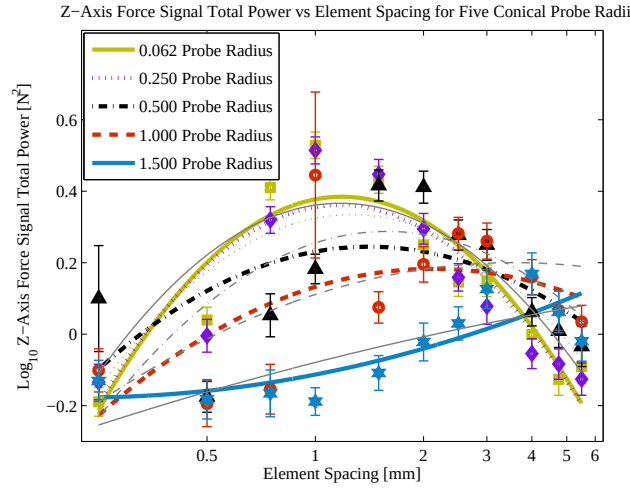
Table 6.4: The maxima of z -axis velocity functions based on 2nd and 3rd order fits to data in a log-log plot. Curvature of the 2nd order fit to z -axis velocity plotted against texture period is also shown as well as the predicted maxima. Results are shown for five conical probe radii.

Factor	DOF	F	p-value
Curvature	3/84	34.74	< 0.0001
Curve Height	3/84	0.70	> 0.05
2nd Order Maxima	3/84	0.53	> 0.05
3rd Order Maxima	3/84	0.34	> 0.05

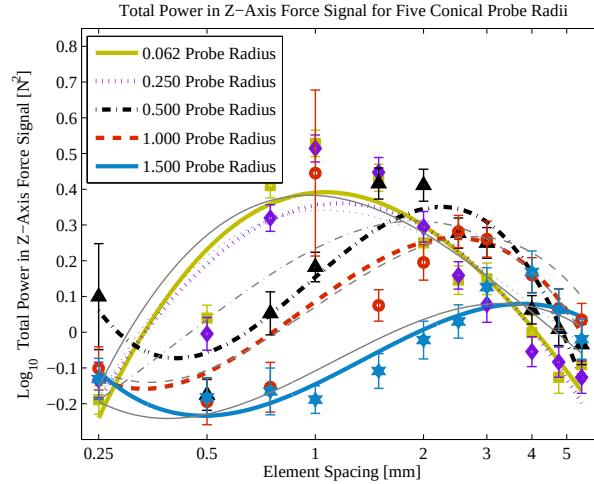
Table 6.5: Significance of cone-shaped probe radius effects on mean z -axis velocity determined using a 1-way ANOVA on curvature, curve height and maxima location of 2nd and 3rd order fits to velocity data in a log-log plot. Only the largest four probe sizes are used.

order fit works well for the smallest probes but larger probes are better fit by a third order equation (See Appendix A, Table A.26 for R^2 values and equations).

The locations of the second and third order maxima for total power can be seen in Table 6.6. The mean absolute difference between third order maxima locations for total power and corresponding maxima for roughness is 0.22 mm. The effect of probe radius on third order, but not second order maxima location is significant for total power, when the largest four probe sizes are analyzed with a 1-way ANOVA. The decreases in second order curvature and curve height which occur with increasing probe size for roughness, are also significant for force signal total power. The locations of $\Phi(I)$ maxima, near the geometric model's predicted DPs, indicate that total power in the force signal is also governed by probe-texture geometry. The decline in the height of the curves at the DP and the decrease in curvature are likely due to the more gradual changes in z -axis height dictated by the CSA as the conical probe's radius increases (see Section 6.1). Small absolute curvature implies



(a)



(b)

Figure 6.4: a.) Second order fit to total power in the z -axis force signal in a log-log plot for dithered conical textures explored with conical probes of 0.0625 to 1.5 mm radius. Probe height was 0.25 mm b.) Third order fit to the same data. Subject roughness estimates, normalized to velocity, are shown as thin gray lines.

small changes in force variability with respect to changes in element spacing. Smaller absolute curvatures with increasing probe size should result in larger thresholds for detecting roughness changes thus JND should increase with conical probe size.

Roughness correlates with power in the FA1 and the FA2 bandwidths equally well. This finding makes it impossible to determine whether one receptor or the other is responsible for roughness

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.06	-1.30	1.04	1.19	1.07
0.25	-1.22	1.04	1.17	1.20
0.50	-0.84	1.68	1.60	2.19
1.00	-0.18	2.68	7.30	2.82
1.50	0.15	3.68	0.22	3.80

Table 6.6: The maxima of the total power in the z -axis force signal functions based on 2nd and 3rd order fits in a log-log plot. Curvature and the predicted maxima are also shown for five conical probe radii.

Factor	DOF	F	p-value
Curvature	3/84	56.36	< 0.0001
Curve Height	3/84	10.58	< 0.0001
2nd Order Maxima	3/84	2.09	> 0.05
3rd Order Maxima	3/84	19.48	< 0.0001

Table 6.7: Significance of conical probe radius effects on total power in the z -axis force signal determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit in a log-log plot. Only the four largest probe sizes were used.

perception. That both bandwidths correlate well suggests that total power in the signal is likely the key determinant of roughness. Factors which increase power in one bandwidth are likely to increase the other proportionally. An experiment which would selectively increase power in only one of the two bandwidths might be useful to isolate the receptor responsible for roughness.

Total power in the z -axis force signal continues to correlate well with roughness for all sizes and shapes of probe examined so far. The strong correlation of velocity and several other measures does not contradict the hypothesis that total power is the property which characterizes roughness. Since force variability is related to these properties, their correlation with roughness, particularly for a relatively small data set, is not unexpected. The use of velocity as a surrogate for force variability when force measurements are unavailable could certainly be considered although, when examined closely, as in Section 3.4, velocity is clearly inferior to total power for characterizing roughness.

6.6 Probe Shape and the JND for Roughness

The constraint surface algorithm is changed when the shape of the probe is changed from spherical to conical, resulting in new probe-texture geometric interactions. This change in geometry has been shown to alter the shape of the psychophysical function for roughness as well the physical properties that characterize it. For example, the absolute curvature of the psychophysical function for roughness is larger for spherical (see Section 5.4, Table 5.1) than it is for conical probes (see Table 6.1 above) for equivalent probe sizes. If absolute curvature of the roughness function is indicative of subjects' sensitivity to changes in element spacing then JNDs for spherical probes should be smaller than those for conical probes.

The conical probe JND experiment examines the threshold at which subjects can determine a difference in texture roughness which results from changes in element spacing. A dithered cone texture surface is used which has elements of the same dimensions used in Section 6.3. Conical probes of 0.25, 0.50 and 1.00 mm radius and a height of 0.25 mm are used. The 0.25 mm radius probe, as discussed in Section 6.2, above, has a constraint surface which is functionally equivalent to that of a point-probe. The 0.50 and 1.00 mm probes have constraint surfaces which are described by the equations in Section 6.2 which apply to probes for which $90^\circ - \delta < \alpha$ and $h_{probe} < el_h$ as seen in Figure 6.1b.

Twelve subjects, seven male and five female, took part in the experiment. Nine of the subjects were right-handed and three were left-handed by self report. Left-handed subjects performed the experiment with their non-dominant hand. All subjects were drawn from Carnegie Mellon University's Psychology Department experimental subject pool and received course credit for performing the experiment. Experiments lasted approximately one hour although no time limit was imposed on subjects.

The experimental protocol was identical with that of Chapter 5, Section 5.6 and used a modified version of Kaernbach's unforced weighted up-down adaptive staircase technique.

JNDs are determined for three different base texture spacings (BTSs) for each probe radius. The base texture spacings associated with a single probe size are presented in random order, as a block. The ordering of block presentation was counterbalanced between subjects to prevent learning effects. Each subject, thus, performed nine JND determinations in total.

The choice of BTSs for the conical probe experiments is based on the predicted DPs for roughness as determined from the equations of Section 6.2 and seen in Table 6.8. The goal is to choose

Probe Radius [mm]	Base Texture Spacing [mm]		
	BT1	BT2	BT3
0.25	0.40	0.60	0.80
0.50	0.70	0.90	1.10
1.00	1.30	1.60	1.90

Table 6.8: Probe radius and base texture spacing used for conical probe JND experiments.

points on the psychophysical function for roughness which are proportionally the same distance from the DP, in order to avoid runaway JNDs (see Section 5.6 for a description of runaway JNDs). This should provide threshold measurements that are roughly comparable, regardless of probe size, in their accuracy. In practice, the choice of BTS is based on preliminary trials over a wide range of spacings which determined the largest BTS for each probe radius which did not result in a runaway JND. The selected BTSs can be seen in Table 6.8.

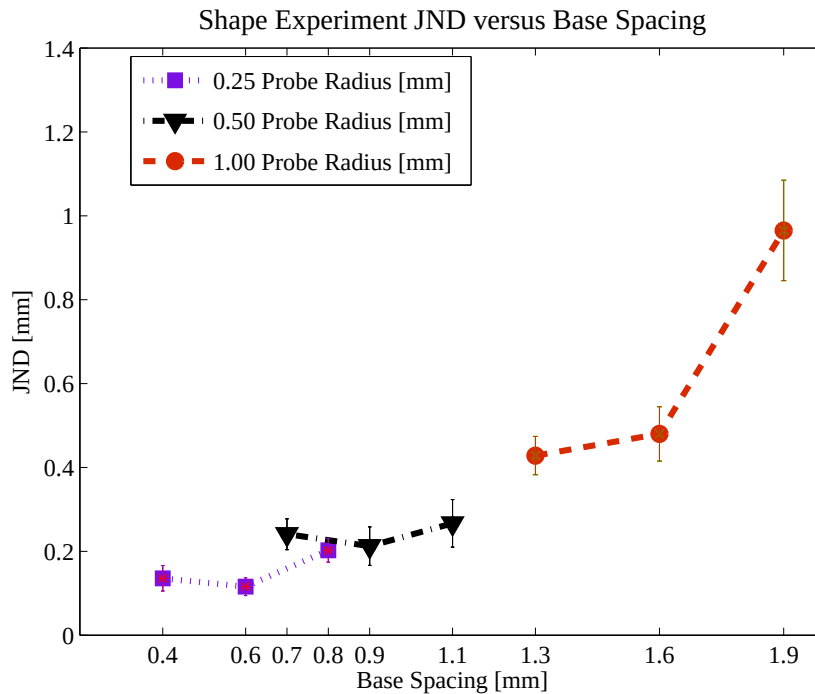


Figure 6.5: JND thresholds for conical probes on dithered truncated conical textures. Base spacings vary depending on probe radius.

The mean JND over subjects for each probe radius and BTS can be seen in Figure 6.5 and Table 6.9. The minimum JND for the 0.25, 0.50 and 1.0 mm probe radii are 0.116, 0.212, and

0.428 mm respectively. These minimum JNDs are larger than those of spherical probes with the same radius (JND = 0.105, 0.209 and 0.317 mm respectively). It is also noted that, for equivalent probe radii and roughly equivalent BTS, the JNDs for spherical probes are also slightly smaller than those for conical probes. These findings may be indicative of the larger amount of noise created by discontinuities in the constraint surfaces for conical probes. Such discontinuities are not present in spherical probe constraint surfaces, resulting in potentially greater sensitivity to changes in roughness.

Probe Radius [mm]	Base Texture JND [mm]		
	BT1	BT2	BT3
0.25	0.136	0.116	0.202
0.50	0.241	0.212	0.267
1.00	0.428	0.480	0.965

Table 6.9: JNDs for conical probe radius–base texture pairings.

The increase in JND with increasing BTS, seen in Figure 6.5 for all probe sizes and seen for the larger BTSs with spherical probes (Section 5.6, Table 5.8) may be attributed to the decrease in sensitivity to changes in element spacing which subjects exhibit as the DP of $\Psi(I)$ is approached by the BTS. This decreased sensitivity is related to the decreased slope of the roughness function at its apex.

While the range of BTS is different for each probe size, the trend of increasing JND with increasing conical probe size, predicted above, appears to be present (see Figure 6.6). This phenomenon can be related to the decreasing curvature of the roughness function which occurs with increasing probe radius. This decrease in curvature is, in turn, a result of decreased force variability with increasing probe size which is itself related to changes in probe-texture geometry (see Section 6.4).

6.7 Conclusions

A change in probe shape from spherical to conical results in small but significant changes to the probe-texture geometry generated by the CSA. The resulting shape of the psychophysical function for roughness is quadratic only for the smallest point-probes while the larger probes now exhibit roughness functions which are best fit by a third order equation. Absolute curvature of $\Psi(I)$ is smaller for conical probes than it is for equally-sized spherical ones.

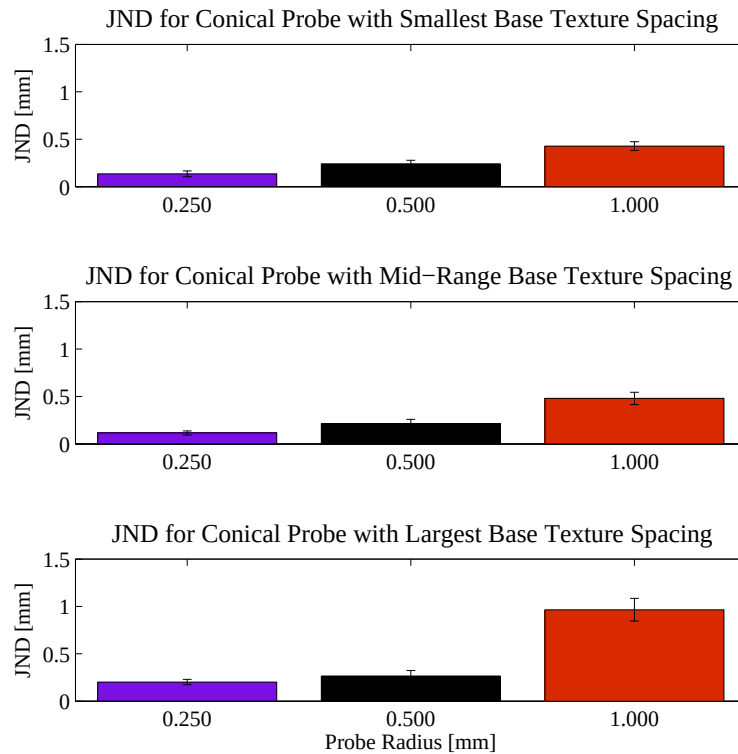


Figure 6.6: JND thresholds for base texture spacings by quintile for three conical probe radii.

The location of the DP for various probe sizes is well predicted by the geometric model for roughness, modified to account for the conical shape of the probe and revised to include probe velocity.

The curvature and height of the roughness functions decrease as probe size increases. This is likely due to changes in the physical property characterizing roughness, the total power in the z -axis force signal, which is also shown to decrease with increasing probe size. The decrease in the force variability is likely due to the more gradual slopes in the constraint surface that result from increasing the probe radius.

Z -axis force variability continues to correlate well with roughness perception, just as it did for sinusoidal textures, trapezoidal textures and dithered conical textures. Since changes in texture and probe geometry do not seem to affect the degree of correlation seen, z -axis force variability, as measured by the total power in the force signal, continues to be the best candidate for the property to use to characterize texture.

Because the curvature of $\Psi(I)$ decreases with increasing probe size for conical probes, it was anticipated that JNDs would increase with probe size. This is a result of the decreasing sensitivity to changes in element spacing that decreased curvature implies. The JND was, indeed, found to increase with probe size. The actual JND values were found to be slightly larger for conical probes than for spherical ones. This was thought to be due to the large amount of noise generated by discontinuities in the constraint surface for conical probes and its effect on subjects' sensitivity to changes in roughness.

The shape of the probe clearly has a significant effect on the form of the psychophysical function for roughness, $\Psi(I)$, and the way in which $\Psi(I)$ responds to changes in probe size. The CSA could be applied to more shapes, the easiest implementations being those that involve radially symmetric shapes. Constraints surfaces using cylinders, radially swept parabolas, and other such probe shapes could easily be designed and might provide an interesting range of textures to explore.

Chapter 7

Dithered Conical Textures and Compliance Effects

7.1 Introduction

There is little work in either the haptics or psychophysical literature about the effects of probe compliance on texture perception. The probe of choice in real studies is usually made of some fairly hard, non-compliant material such as Delrin plastic [65, 66, 76]. Such a probe is presumably chosen by experimenters based on an assumption that a hard probe more reliably transmits texture vibrations to the user's hand than a soft one. A harder probe, such as one made from steel, might prove even more effective. However, since manufactured texture plates are expensive and susceptible to wear from hard probes, this choice is rarely made.

In virtual textures, the probe-texture contact will, of necessity, be fairly compliant, since most haptic devices are incapable of rendering very stiff surfaces.

While the role of probe compliance in texture roughness perception is unstudied, there is indirect evidence that compliance plays a significant role in the perception of virtual surfaces. For example, the physical end-effector appears to play a role in roughness perception with a PHANTOMTM haptic device, perhaps due to features of its compliance or resonant frequency [107]. Since compliance will affect frequency cues carried by probe vibrations to the hand, and since studies demonstrate that frequency cues play a role in allowing subjects to distinguish textured features [148, 153], changes in compliance may be expected to change subjective roughness.

Evidence that probe-based interaction is more sensitive than the fingerpad for fine textures [74], suggests that the lower compliance (higher stiffness) of the probe actually aids in discriminating between high frequency signals from small period textures.

Softer probes may also confound a subject's ability to determine the amount of force they are applying, especially if force is being judged by hand or finger displacement (proprioception) and not actually sensed directly. If, as it is thought, subjects use knowledge of the force they are applying to make roughness judgements [108], a softer probe may also make roughness judgements more difficult and erratic.

Compliance certainly affects the ability to feel small changes in surface geometry since the relative stiffness of two surfaces affects a subject's ability to feel a step deformity; decreasing stiffness reduces this capability [145].

The amount of stiffness a haptic device can generate is often cited as one of its fundamental operating characteristics [42]. The effect of modifying the stiffness of the probe-texture interface is therefore of interest, since it demonstrates the way in which changes in roughness perception may be related to haptic device capabilities. If stiffness has a significant effect on roughness perception, this could impact future device design and affect the interpretation of results from differing haptic devices.

It is expected that low compliance (stiffer) probes will transmit changes in contact forces more accurately by generating larger and more rapidly changing forces producing a higher power force signal and wider vibrational frequency ranges. Since roughness perception when using a probe relies on vibrational effects, stiffer probes should produce a perception of greater roughness, all other conditions being equal.

7.2 The Penalty Method and Compliance

A simple approach to dealing with probe-texture compliance, is to consider the common method for dealing with contact force determination in haptic displays. This technique, the penalty method, calculates the force applied to the haptic interaction point (HIP), as a function of penetration distance, d , of the probe into the surface,

$$F = f(d), \tag{7.1}$$

where F is usually proportional to d

$$F = -kd. \tag{7.2}$$

Occasionally a damping component is added:

$$F = c\dot{x} - kd. \quad (7.3)$$

Penetration distance can be defined in a number of ways. It may be found as the distance from the nearest surface to the tip of the probe or it may be the distance along the path of the probe to its entry point on the surface. In the current experiment it is defined as the distance of the HIP below its desired position on the z axis.

Generally, the probe is considered infinitely stiff and the texture surface is considered compliant. However, in reality, the stiffness resides in the interaction between probe and texture. The penetration depth algorithm can therefore be thought of as an infinitely stiff surface deforming a compliant probe or *vice versa*. Since the penetration depth algorithm is already a component of the constraint surface model it is easy to vary probe compliance by modifying the proportional gains used for hard contacts.

7.3 Roughness Magnitude Estimation Experimental Design

In order to investigate the effects of compliance on texture perception the psychophysical function, $\Psi(I)$, for roughness was determined for four different levels of compliance. Changes in the maxima and curvature of $\Psi(I)$ were recorded and analyzed. By observing and analyzing roughness perception over a range of element spacings, it was possible to get a picture of the effects of compliance, not just at a single element spacing, but over a wide range of texture geometries.

A spherical probe with a radius of 0.5 mm was used for all compliance experiments. This size of probe was selected since it was in the center of the range used for the probe size experiments of Chapter 5, allowing for direct comparison with previous results. The constraint surface algorithm (CSA) of Chapter 5 was used to render dithered conical textures with 11 different element spacings. These spacings covered the same range of 0.5 to 5.5 mm used in that chapter. The element height, ($C_h = el_h = 0.42$ mm), side angle, ($\alpha = 53^\circ$), base radius ($R_{base} = 0.52$ mm), and top radius, ($R_{top} = 0.23$ mm), were the same as well.

The four levels of compliance under study (3.0, 5.0, 10.0, and 15.0 N/mm) were selected to cover as large a range as possible while maintaining device operability and stability. The minimum possible operational stiffness was approximately 3 N/mm. Lower values ran the risk of the device manipulandum pushing through the simulated textured surface, driven by the force of the subject's

hand, and making hard contact with the fixed shell of the system hardware. Values higher than 15 N/mm resulted in unwanted vibrations, especially with small period textures.

Changes in probe compliance were implemented by modifying the proportional gains used for translational hard contacts. Proportional gains for rotation were left constant at 25 Nm/radian. Derivative gains for both translation and rotation were left at their nominal values of 0.04 N/mm/s and 0.5 N/radian/s respectively.

Experimental setup was identical in all other ways to that of Chapter 5. A total of 11 texture spacings and four probe levels of probe compliance yielded 44 probe-texture combinations. Each combination was encountered 3 times by subjects for a total of 132 trials in a single subject experiment. The trials were not blocked by probe type but were presented in random order to avoid learning effects and to ensure that subjects used a single scale for all levels of probe compliance. This allowed comparison of roughness magnitudes across all probe conditions.

A total of 21 subjects participated in the compliance experiment; six females and 15 males. A total of 16 subjects reported themselves as right-hand dominant while 5 were left-handed. Left-handed subjects performed the experiment with their non-dominant hand. Subjects were all psychology undergraduates enrolled in the psychology department at Carnegie Mellon University. They completed the experiment for course credit.

Subjects were seated approximately 500 mm from the graphical display used to enter the roughness estimates, with the MLHD on their right-hand side. The texture was only displayed haptically. White noise, played through headphones ensured that audio cues were not available to assist in texture discrimination.

Subjects were notified that they would encounter the textures as a series of trials. Trials were presented in two blocks: a demonstration block and an experimental block. The demonstration block consisted of 24 trials, in which six texture spacings, spanning the range of 0.5-5.5 mm, and all four probe compliances were displayed. After the demonstration block, actual magnitude estimation began. Subjects entered a numeric value using a computer keyboard and were informed of their progress by a reported trial number but otherwise received no other feedback on performance. Subjects were not instructed how to feel the texture and were given no restrictions on time. Although experiments were slated to run for one hour, most subjects finished in much shorter time frames.

Subjects were told that they could assign roughness estimates to any positive range of numbers but that larger numbers were to reflect larger values of roughness and smaller numbers were

to represent smaller values of roughness. They were specifically asked not to use 0 or negative numbers.

Recorded data consists of subject roughness magnitude estimates along with 1000 Hz continuous sampling of the HIP position and the commanded z -axis forces.

7.4 Compliance Effects and Roughness

It is hypothesised that changing compliance will have a significant effect on roughness perception and the shape of the psychophysical function. Since a more compliant probe may result in the generation of a much smaller range of forces during probe-texture interaction, subjects will feel attenuated forces at their fingertips and should thus feel smaller subjective roughness. If texture roughness is related to total force signal power, as determined in Chapter 3, then the element spacing at which maximum roughness occurs should not be affected by changes in compliance. The spacing at which maximum power occurs should still be dictated by probe-texture geometry, even if power, itself, is diminished.

Figure 7.1 shows a second order fit on a log-log plot to magnitude estimation data made by subjects using four different levels of probe compliance. It can be seen that the roughness magnitudes rise and then fall as element spacing increases, following the same “U”-shaped, roughly quadratic shape seen in Chapter 5 for dithered conical textures. This is not unexpected since, for the 10 N/mm compliance level, the texture and probe are identical to those used in Chapter 5.

Probe Compliance [N/mm]	2nd Ord. Curv.	2nd Ord. Hght.	2nd Ord. Max. [mm]	3rd Ord. Max [mm]
3.00	-0.37	4.53	1.93	2.00
5.00	-0.83	6.20	1.78	1.72
10.00	-1.08	9.98	1.82	1.71
15.00	-1.24	12.81	1.89	1.66

Table 7.1: The maxima of the dithered conical texture roughness estimate functions based on 2nd and 3rd order curves. Curvature and height of the 2nd order fit to roughness estimates plotted against texture period are also shown. Results are shown for four levels of compliance.

It is immediately obvious, however, that changing the compliance of the probe, changes the shape of $\Psi(I)$ in a predictable fashion. Decreasing probe compliance (*i.e.* increasing levels of stiffness), results in increased roughness. The increase in roughness is particularly marked at the point

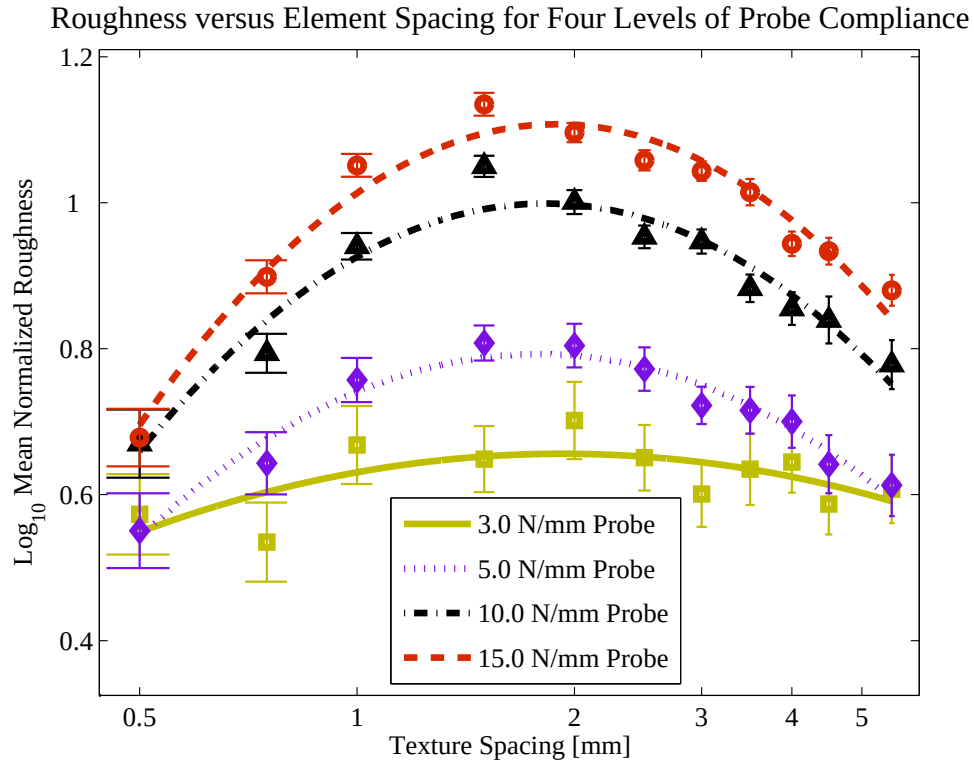


Figure 7.1: Second order fit on a log-log plot, to mean texture roughness magnitude estimates for probes of four different compliances. The estimates are normalized over all subjects using the mean estimate over all subject trials.

of maximum roughness for each probe's $\Psi(I)$ and less marked at the upper and lower extremes of element spacing. Table 7.1 shows the cross-subjects mean maximum roughness levels as measured by the curve height of the second order fits to the magnitude estimation data for each level of compliance. Since levels of compliance were randomized, as well as the order of element spacing, subjects used only one scale to assess roughness during the entire experiment. Relative scaling of roughness is, therefore, preserved between the $\Psi(I)$ functions for probes of differing compliance. Table 7.2 shows that probe compliance has a significant effect on curve height.

The second order fit to the data also improves with decreasing compliance, ranging from an R^2 value of 0.46 for the 3 N/mm probe to 0.96 for the 15 N/mm probe. (A third order fit is only slightly better, with R^2 ranging from 0.47 to 0.98. See Appendix A, Table A.27). The reasons for this are twofold.

First, $\Psi(I)$ appears to be a highly curved function for high levels of stiffness but flattens to resemble a straight line for very low levels of stiffness. Evidence for this can be seen in Table 7.1

Factor	DOF	F	p-value
Curvature	3/80	7.46	< 0.001
Curve Height	3/80	65.32	< 0.0001
2nd Order Maxima	3/80	1.05	> 0.05
3rd Order Maxima	3/80	0.14	> 0.05

Table 7.2: Significance of probe size effects on curvature and maxima of a 2nd and 3rd order fits to roughness data in the compliance experiment, determined using a 1-way ANOVA.

which shows that absolute curvature increases steadily with stiffness from 0.37-1.24 for probes of 3-15 N/mm stiffness respectively. This increase in curvature with decreasing compliance is significant when examined with a 1-way ANOVA (Table 7.2). As described previously, large absolute curvature implies greater sensitivity to changes in roughness, since change in roughness with respect to element spacing is greater for most points on such a curve. Stiffer probes, therefore, appear to impart greater sensitivity to changes in roughness.

The second reason for better second order fits with increasing stiffness is related to between-subject variation in roughness estimates at varying levels of compliance. Observing the error bars on $\Psi(I)$ for the various probes (Figure 7.1), it can be seen that the variability of roughness estimates increases substantially as compliance increases. This increase in the range of perceived roughness for identical element spacings also suggests that increasing compliance reduces subjective sensitivity to roughness. The increase in variability exists over the entire range of element spacings although it is largest at the extremes of spacing and smallest at the drop point.

It is interesting to observe that the $\Psi(I)$ functions for different levels of compliance show a tendency to come together for the largest and smallest element spacings. These points are ones at which most subjects are reporting low roughness magnitudes. It is possible that, due to the probe-texture geometry at these element spacings, the roughness levels experienced by subjects are similar regardless of compliance. At these spacings, subjects may be perceiving the texture as completely smooth. Since they are not permitted to use 0 as a roughness magnitude, subjects assign some very small number to such smooth textures and thus, for very small and very large element spacings, roughness appears identical between compliance levels.

The element spacing at which the drop point occurs is virtually identical for all levels of compliance (See Table 7.1). The DP for a 0.5 mm spherical probe on a dithered conical texture was

determined, in Section 5.4, to be 1.93 based on a second order fit to data. DPs in this experiment ranged from 1.78-1.93, with no apparent effect from probe compliance as measured with a 1-way ANOVA (see Table 7.2). Evidently, the drop point is related only to probe-texture geometry and is unaffected by changes in compliance.

The decrease in relative roughness, for identical probe size and shape at identical texture element spacings, shows that increasing compliance reduces subjective roughness. The reason for this could potentially be related to the physical property which is characterized as roughness – namely, the total power in the force signal (see Section 3.4). Since increasing compliance reduces the amount of force generated for equivalent displacements of the HIP, the overall power in the force signal should also decline.

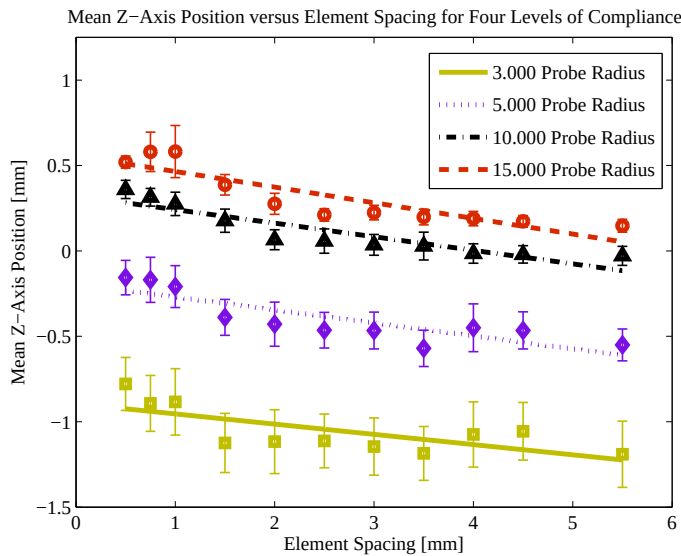


Figure 7.2: Mean over all subjects of z -axis position at each element spacing during magnitude estimation with four different levels of compliance. A linear fit is shown.

Of course, the penetration depth algorithm generates forces proportional to displacement. Thus, when surfaces are more compliant, displacements of the HIP can be larger too. This effect can be seen in Figure 7.2. The mean position of the HIP in the z axis is lower when compliance is lower. As expected, position also falls with increasing element spacing, since the probe spends more time on the base plane of textures with larger element spacings. Interestingly, for the two lowest compliance levels (15.0 and 10.0 N/mm) the mean z -axis position over all subjects and spacings is positive (0.317 ± 0.006 , 0.114 ± 0.005 mm) while for the two highest compliance levels (5.0 and 3.0 N/mm) it is negative (-0.393 ± 0.006 , -1.051 ± 0.005 mm). Also of interest is that, while the change of

stiffness from 15 to 10 N/mm results in only a small change in penetration depth, the change in stiffness from 10 to 5 and 5 to 3 N/mm results in a larger one.

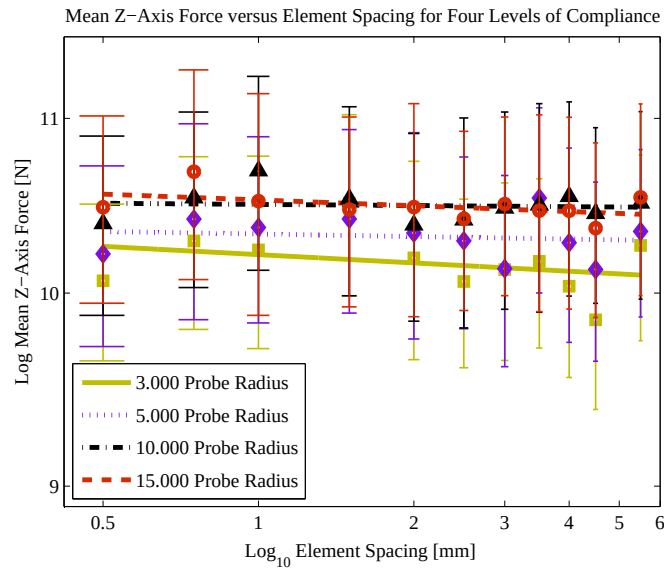


Figure 7.3: Mean over all subjects of z -axis force applied at each element spacing during magnitude estimation with four different levels of compliance. A linear fit in the log-log plot is shown.

If subjects apply the same amount of force to the manipulandum for all levels of compliance, the HIP should be displaced proportionally. Thus, even though a probe or surface is softer, the force generated by the probe-texture interface will only be reduced if subjects realize this and compensate by decreasing applied forces accordingly. Examining Figure 7.3 it appears that the mean force applied by subjects varies little with compliance or element spacing. A 1-way ANOVA on the mean force applied demonstrates that there is no significant effect from changing levels of compliance. The trend, however, appears to demonstrate that subjects do reduce their applied force slightly when presented with a more compliant surface.

The force output to the manipulandum can be divided into the force, F_{geom} , resulting from the variation in surface profile due to probe-texture geometric interaction and the force, F_{pen} , generated by HIP penetration below the base plane of the texture. Force variability, as measured by the power in the force signal, results only from F_{geom} . As compliance increases, so to, does the HIP's penetration depth beneath the base plane, increasing F_{pen} while F_{geom} remains the same. The ratio of F_{geom} to F_{pen} decreases. The variability in the force signal power, as a proportion of the total force is thus reduced, potentially reducing the sensation of roughness.

The penetration depth algorithm is not applicable directly to real textures. However, if the force signal from real texture surface geometry is considered to be F_{geom} and the force signal from large-scale surface deformation is considered to be F_{pen} , then, for a compliant surface which deforms on a large scale, the ratio of F_{geom} to F_{pen} could be expected to diminish in the same way for real and virtual textures, reducing the sensation of roughness. An investigation of the effects of changing compliance on roughness estimates in real textures might be useful to confirm this.

With virtual texture, the effects of increased compliance might be counteracted by increasing the height of the elements, thereby increasing the relative force contribution of surface geometry to the overall forces experienced by subjects.

7.5 Compliance Effects and the Physics of Roughness Perception

In Chapter 3 the physical property which best characterized roughness for sinusoidal gratings was found to be the total power in the z -axis force signal. Subsequent experiments using trapezoidal gratings, dithered conical textures, and cone-shaped probes did not unambiguously demonstrate the same finding, although correlation was still found to be high between the physical function, $\Phi(I)$, for total power and the psychophysical function for roughness, $\Psi(I)$ (See Sections 4.5, 5.5, and 6.5).

In all of the experiments so far, changes in the shape of the psychophysical function for roughness are reflected in changes in the shape of the physical function for total power. The point of maximum roughness and the curvature of both functions follow the same trends with respect to changes in probe size and shape. In the preceding section (Section 7.4), identical probes with differing levels of compliance, interacting with the same dithered conical texture, have $\Psi(I)$ s which all have approximately the same DP. However, these functions have decreasing absolute curvature as compliance increases. Subsequently, similar findings might be expected for a physical property's $\Phi(I)$ if it, indeed, characterizes roughness.

Examining a representative sample of z -axis position recordings for each level of probe compliance, over the full range of element spacings (See Figure 7.4), it can be seen that, for constant element spacing, the amplitude of motion increases with decreasing compliance. As element spacing increases, the point of maximum amplitude appears to be at approximately 2.0 mm for all levels of compliance. This is close to the determined DP for all four levels of compliance as determined during the magnitude estimations of Section 7.4 above (See Table 7.1).

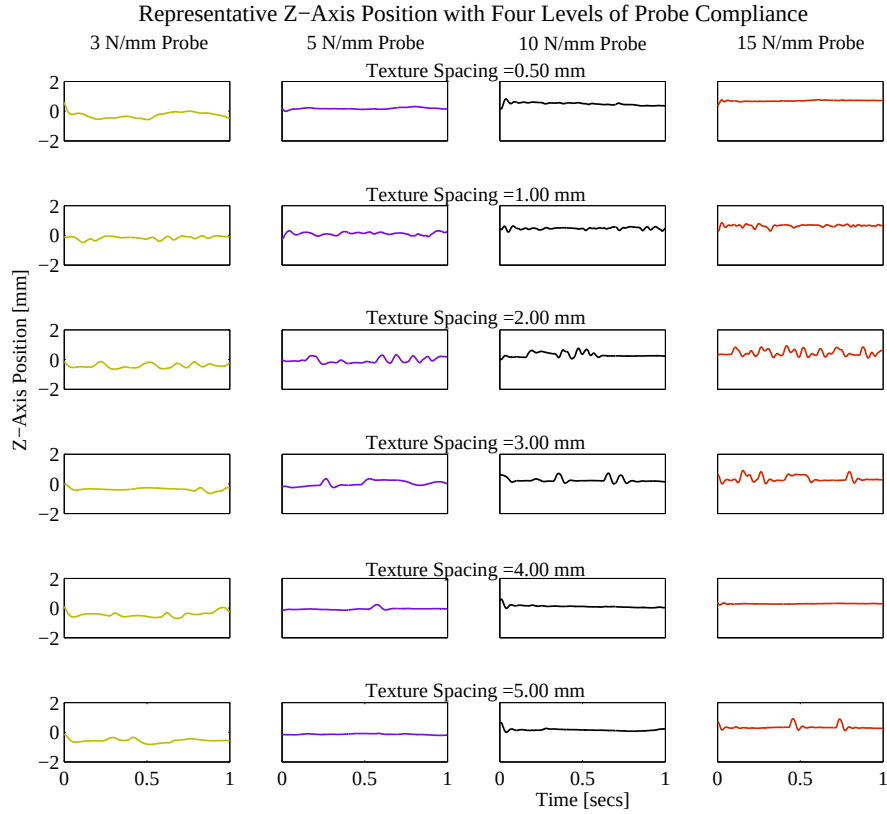


Figure 7.4: Representative one second samples of z -axis position recordings (1000 Hz) for four levels of probe compliance across the range of texture element spacings.

Examining the correlation coefficients between roughness and the physical properties studied in earlier experiments in this thesis, calculated according to the techniques laid out in Section 3.4, it can be seen that relatively good correlation once again exists for a wide range of measures (Table 7.3). The best correlated physical function, across all levels of compliance, is velocity although acceleration and total power in the z -axis force signal are also well correlated.

In order to compare plot curvature and height for the velocity $\Phi(I)$, a second order fit in a log-log plot was chosen to represent the data. The curvature, height and drop point for $\Phi(I)$ can be seen in Table 7.4 while the same values for the roughness $\Psi(I)$ are found in Table 7.1. The location of the DP for velocity, ranging over element spacings of 1.79 to 1.89 mm, is nearly identical to that for roughness, which ranges from 1.79-1.93 mm. The location of the DP is not significantly affected by changes in compliance, as tested by a 1-way ANOVA, for either roughness or z -axis velocity.

	3 N/mm Probe		5 N/mm Probe		10 N/mm Probe		15 N/mm Probe	
Parameter	Corr. C.	p	Corr. C.	p	Corr. C.	p	Corr. C.	p
Mean Position	0.37	> 0.05	0.28	> 0.05	-0.05	> 0.05	-0.15	> 0.05
Velocity	0.83	< 0.005	0.96	< 0.0001	0.99	< 0.0001	0.97	< 0.0001
Acceleration	0.83	< 0.005	0.94	< 0.0001	0.99	< 0.0001	0.96	< 0.0001
Energy	0.79	< 0.005	0.93	< 0.0001	0.96	< 0.0001	0.91	< 0.0005
Position Std	0.11	> 0.05	0.49	> 0.05	0.80	< 0.005	0.93	< 0.0001
Mean Force	0.23	> 0.05	0.32	> 0.05	0.13	> 0.05	-0.24	> 0.05
Max Power	-0.04	> 0.05	0.10	> 0.05	0.90	< 0.0005	0.91	< 0.0001
Freq. Max Pow.	0.49	> 0.05	0.89	< 0.0005	0.92	< 0.0001	0.90	< 0.0005
FA1 Power	0.81	< 0.005	0.85	< 0.001	0.97	< 0.0001	0.93	< 0.0001
FA2 Power	0.73	< 0.05	0.85	< 0.001	0.94	< 0.0001	0.94	< 0.0001
Total Power	0.83	< 0.005	0.85	< 0.001	0.97	< 0.0001	0.94	< 0.0001

Table 7.3: Correlation coefficients for various physics property measures with the psychophysical function for roughness for dithered conical textures with four levels of probe compliance. Outliers have been removed from maglev and subject data.

Compliance [N/mm]	2nd Order Curv.	2nd Ord. Hght. [mm]	2nd Ord. Max. [mm]	3rd Ord. Max [mm]
3.00	-0.74	3.92	1.79	1.92
5.00	-1.32	5.04	1.83	1.90
10.00	-1.98	8.49	1.88	1.87
15.00	-2.08	11.81	1.89	1.81

Table 7.4: The maxima of dithered conical texture mean z -axis velocity functions based on 2nd and 3rd order curves. Curvature of the 2nd order fit to roughness estimates plotted against texture spacing is also shown. Results are shown for four levels of compliance.

This striking similarity between DPs suggests that the probe-texture geometry effects on velocity are unaffected by changes in compliance.

Z-Axis Velocity versus Element Spacing for Four Levels of Probe Compliance

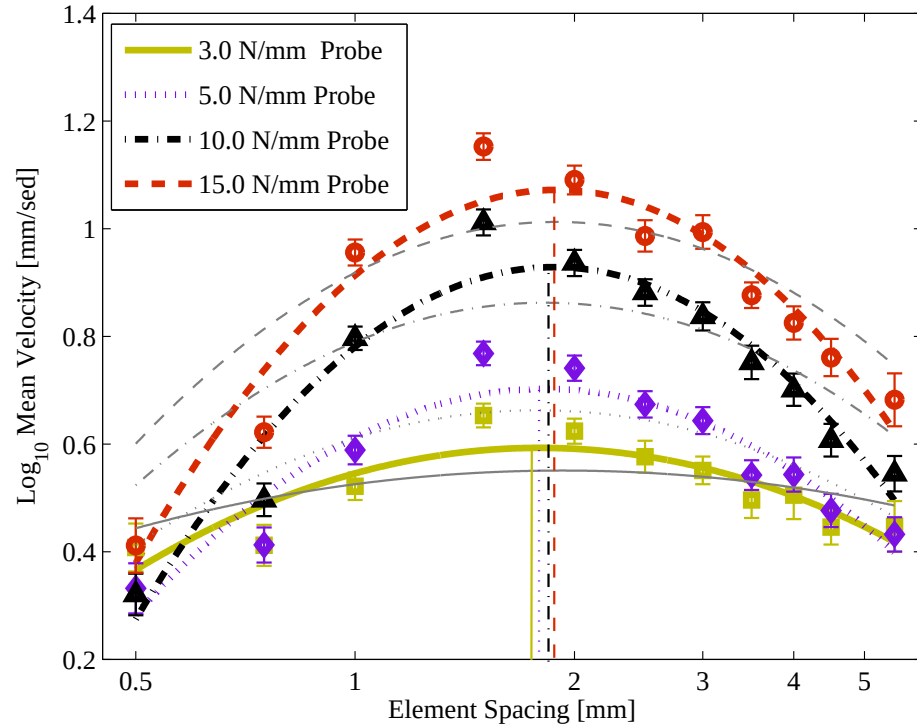


Figure 7.5: Second order fit in a log-log plot to mean z -axis velocity plotted against texture spacing for four levels of compliance. Subject roughness estimates, normalized against z -axis velocity, are shown as thin gray lines for comparison. Vertical lines indicate the maxima of the velocity fits.

Factor	DOF	F	p-value
Curvature	3/80	19.02	< 0.0001
Curve Height	3/80	37.58	< 0.0001
2nd Order Maxima	3/80	0.44	> 0.05
3rd Order Maxima	3/80	0.17	> 0.05

Table 7.5: Significance of probe size effects in the compliance experiment determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit to mean z -axis velocity.

What is affected is the magnitude of the velocity $\Phi(I)$ as well as the roughness $\Psi(I)$ at the drop point and throughout the range of spacings. Increasing compliance results in a lower amplitude function for both roughness and velocity. Lower compliance reduces the size of the forces experienced by the user thus reducing the velocities and roughness experienced by the subjects.

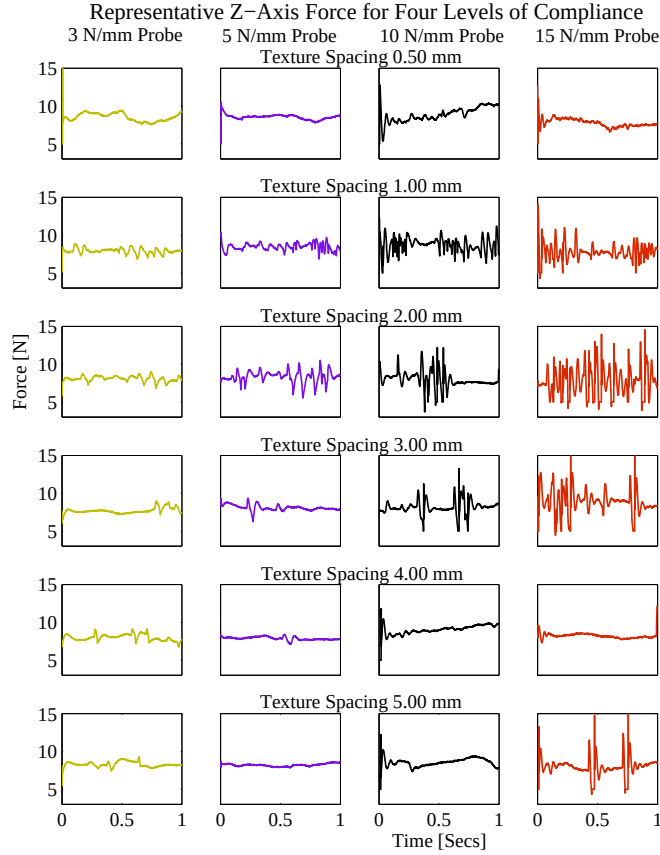


Figure 7.6: Representative one second samples of z -axis force recordings (1000 Hz) for four levels of probe compliance across the range of texture element spacings.

The z -axis forces, which have been implicated as the physics property perceived as texture, are shown in a representative plot of one second recordings which span the range of compliance and element spacing used in this experiment (Figure 7.6). The forces increase to a maximum at an element spacing around 2 mm just as the position amplitude did. The drop points of the $\Phi(I)$ s for total power in the PSD of the z -axis force signal also correspond quite well with the $\Psi(I)$ s for roughness, ranging from 1.52 to 1.91 mm. The DP for the lowest compliance should be assumed inaccurate since the second order curve is very nearly a straight line for total power. Once again, there is no significant effect of probe compliance on the DPs for total power (see Table 7.7). Clearly probe-texture geometry maintains its effect on the DP at all levels of compliance for force signal power in the same way it does for roughness and velocity. Similarly, the magnitude of the $\Phi(I)$ for total power decreases with increasing compliance, especially at the DP but also over most of

Z-Axis Force Total Power vs. Element Spacing for Four Levels of Compliance

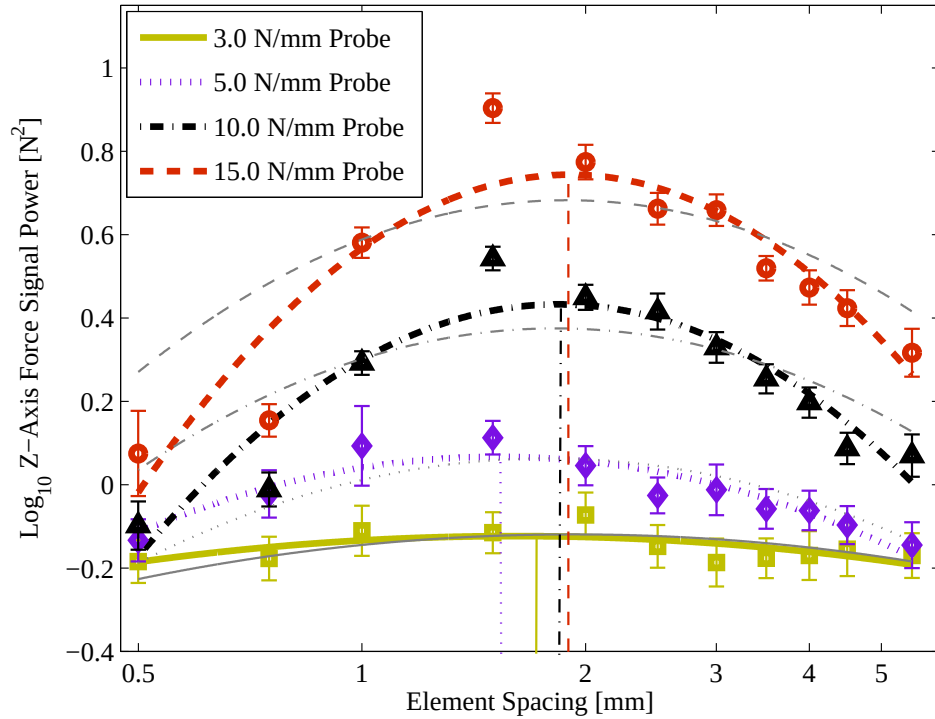


Figure 7.7: Second order fit to the total power in the z -axis force signal plotted versus texture spacing for four different probe sizes. Subject roughness estimates, normalized to the total power curves, are shown as thin gray lines for comparison.

the range of element spacings as well. This suggests that there is a reduction in force variability occurring with increasing compliance and that this is perceived by subjects as a smoother surface.

Interestingly, for roughness, velocity, and force power, function magnitudes tend to converge at the extremes of the measured texture range. At these points, the probe-texture geometry is not playing a significant role in the perceived texture. At small element spacings, elements are close together and the probe rides along a smooth surface, regardless of compliance. At large spacings, elements are encountered infrequently and, again, the probe rides along a relatively smooth surface. Thus, at these points, subjects experience a flat surface which differs only in compliance between trials. Since roughness is approximately the same here, for all compliance levels, it appears that compliance itself is not the physical property which characterizes roughness. Rather, it is a confounding factor, modifying the way in which the physical factors involved in roughness perception are produced.

Compliance [N/mm]	2nd Ord. Curv.	2nd Ord. Hght. [mm]	2nd Ord. Max. [mm]	3rd Ord. Max [mm]
3.00	-0.24	0.75	1.61	1.25
5.00	-0.77	1.17	1.52	1.28
10.00	-1.89	2.71	1.84	1.91
15.00	-2.26	5.55	1.90	1.95

Table 7.6: The maxima of the dithered conical texture total power in the z -axis force signal based on 2nd and 3rd order fits in a log-log plot. Curvature and height of the 2nd order fit to total power plotted against texture spacing is also shown. Results are shown for four levels of compliance.

Factor	DOF	F	p-value
Curvature	3/80	47.04	< 0.0001
Curve Height	3/80	99.49	< 0.0001
2nd Order Maxima	3/80	1.53	> 0.05
3rd Order Maxima	3/80	1.67	> 0.05

Table 7.7: Significance of probe size effects in the compliance experiment, determined using a 1-way ANOVA on curvature and maxima of a 2nd and 3rd order fit in a log-log plot to total power in the z -axis force signal.

For both velocity and force signal power, the curvature of the $\Phi(I)$ functions is significantly affected by probe compliance (Tables 7.5 and 7.7). The trend of decreasing curvature with increasing compliance matches that of the roughness function. Clearly, a decrease in either of these two physical properties is perceived as a decrease in roughness.

It is not as clear which physical property most accurately characterizes roughness. Correlation between $\Phi(I)$ and $\Psi(I)$ is high for velocity, acceleration, and energy, as well as the power in the FA1 and FA2 force signal bandwidths, the total power and the frequency of the maximum in the force signal PSD (Table 7.3). Any property, whose DPs, curvature and relative magnitudes are similar to roughness might, thus, be chosen to represent roughness. Since total power is well-matched with roughness in all of the experiments described so far, while other factors have not been as consistent, it still seems the best candidate for the property which characterizes roughness.

7.6 Compliance and the JND for Roughness

The effects of compliance on roughness perception have implications for the threshold at which changes in element spacing can be detected. Increasing compliance results in a $\Psi(I)$ with smaller curvature and lower magnitude, and appears to increase the variability in roughness magnitude estimations. It has no effect on the element spacing of the DP. These results lead to an expectation that the JND for roughness will increase with compliance, particularly for base texture spacings which are farther from the DP where the slope of the psychophysical function is usually the greatest.

The JND experiment for compliance was performed using Kaernbach's unforced weighted up-down adaptive staircase technique, following the procedures documented in Section 2.4. The choice of base texture spacings (BTS) was again driven by a desire to avoid runaway JNDs (see Section 2.4 for details). The spacings chosen (0.5, 0.65 and 0.80 mm) represented the lower end of the BTS range used in the JND experiments for dithered conical textures with spherical and conical probes, avoiding the upswing seen for larger BTS JNDs seen in these experiments. This upswing was attributed to the flattening of the psychophysical function near the drop point (or alternatively, to undetected runaway results). By avoiding it, this experiment concentrated on what should be the most reliable minimum JND results.

Twelve subjects performed 3 blocks of JND trials, one for each level of compliance tested. The ordering of these blocks was counter-balanced to compensate for learning effects. Within each block, 3 separate JNDs at the 3 different base spacings were performed. The subjects were self-selected from a pool of psychology students who received course credit for the study, or they were paid student volunteers. All subjects (3 female, 9 male) were right-handed by self-report.

JND varies both with base spacing and with the compliance of the probe used to explore the surface. Figure 7.8 shows that, for the range of base spacings shown, JNDs decline slightly as spacing increases (see Table 7.8 for actual values). This decline is not statistically significant, as can be seen from the overlapping bars of the standard error.

While the JNDs of the two low compliance probes are not significantly different from each other at any of the BTSs, the most compliant probe requires a significantly higher change in spacing for subjects to notice a change in roughness (See Figure 7.8). An equivalent change in texture geometry will generate smaller amounts of force signal power if a softer probe is used to explore the surface. Thus, assuming that force signal power characterizes roughness, lower levels of compliance will result in higher thresholds.

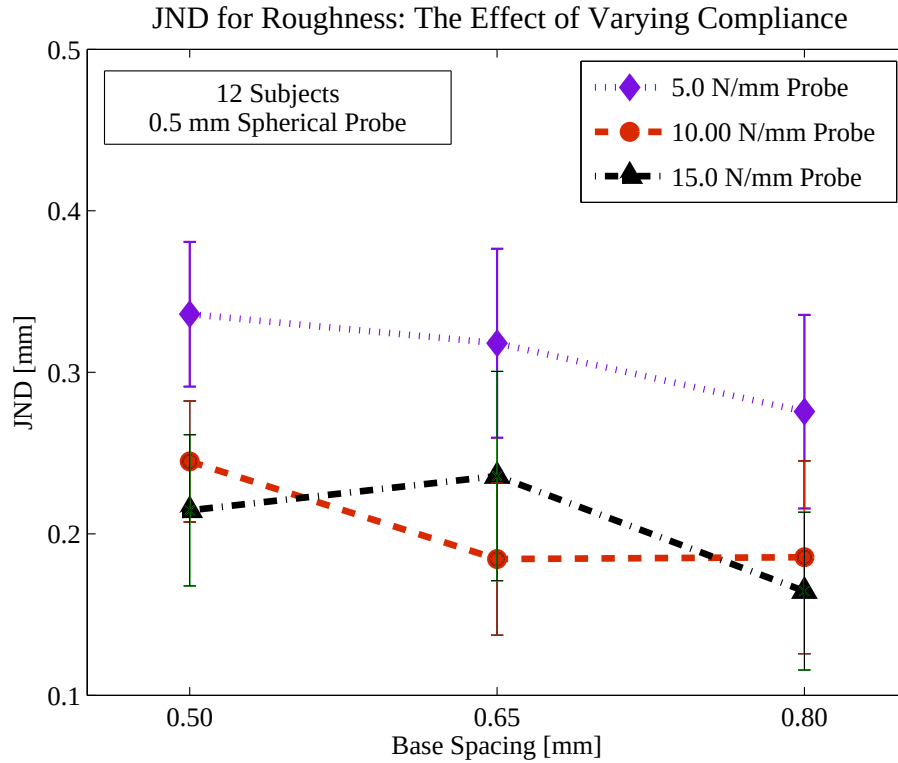


Figure 7.8: Just noticeable difference in roughness for changes in element spacing for probes with three different levels of compliance.

Probe Compliance [N/mm]	Base Texture JND [mm]		
	BTS=0.50 mm	BTS=0.65 mm	BTS=0.80 mm
5.0	0.336	0.318	0.276
10.0	0.245	0.184	0.186
15.0	0.215	0.236	0.165

Table 7.8: Just noticeable differences for probe compliance–base texture pairings.

An increase in compliance appears to diminish subjects' ability to discriminate between textures based on the roughness due to differences in element spacing. It is interesting to observe that the 15 and 10 N/mm probes have JNDs that are statistically indistinguishable. It has also been observed (Section 7.4) that the 15 and 10 N/mm probes have $\Psi(I)$'s which are closer in magnitude than the 10 and 5 N/mm probes. This suggests that there may be a compliance level, beyond which, little change in roughness perception occurs, all other factors being equal.

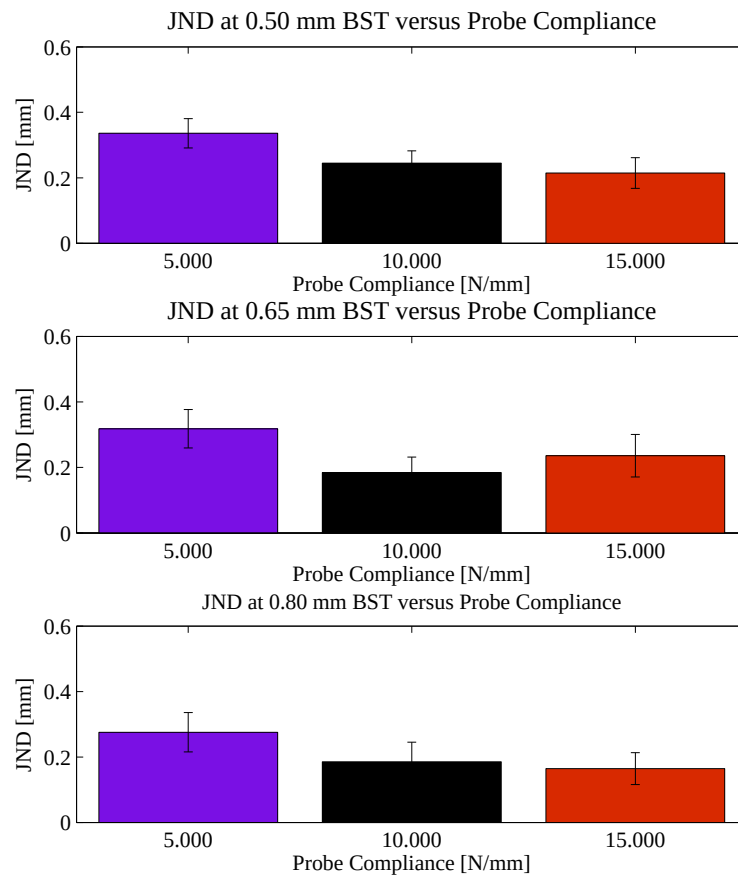


Figure 7.9: Just noticeable difference in roughness versus probe compliance for the same levels of base spacing texture.

7.7 Conclusions

Compliance is a significant confounding factor with regard to roughness perception. Increases in compliance lead to decreases in the magnitude of roughness perception, particularly near the drop point and less so at large and small element spacings. Increased compliance also diminishes the curvature of the psychophysical function for roughness, with the highest compliance levels leading to a function which approaches a horizontal line. On the other hand, changes in compliance appear to have little effect on the element spacing at which maximum roughness occurs.

It appears that compliance alters the magnitude of the forces involved in roughness perception but does not substantially alter the way in which probe-texture geometry generates these forces. Maximum roughness is predicted by the revised geometric model to be at approximately 1.9 mm

element spacing for a 0.5 mm radius spherical probe on the dithered conical textures used (assuming a planar velocity of approximately 50 mm/sec). This DP is observed for all levels of compliance studied.

Changes in the roughness function's magnitude and curvature are reflected in changes in several of the physical properties examined. This includes the total power in the z -axis force signal, providing further confirmation that it is the property which best characterizes roughness.

The JND for roughness appears to increase with compliance. This is probably related to the decrease in curvature of the roughness perception curve with increasing compliance. As curvature decreases, so to does discriminability between textures. The JNDs for the 10 N/mm, 0.5 mm radius probe in this experiment (see Table 7.8) are consistent with the JNDs found for the same size and compliance probe found in Section 5.6. Between-subject variability appears to be low for these JND determinations, substantiating these findings.

It is interesting to note that the stiffness of many haptic devices is at the lower end of the range examined in this experiment. Notably, the PHANTOMTM device has a maximum measured stiffness of 2 N/mm [19]. With this level of stiffness the psychophysical function for roughness would likely resemble a nearly horizontal line. This may help to explain the findings of those researchers who found $\Psi(I)$ to be a highly variable, nearly linear, function using a PHANTOMTM haptic device and sinusoidal grating textures [68, 91, 107].

Chapter 8

Texture Perception and the Effects of Friction

8.1 Introduction

Friction is one of the forces encountered when exploring a textured surface with a probe and as such, may play a significant role in the perception of roughness. Friction is usually considered to be resistance to movement along a surface and, on a horizontal surface, is usually simulated as a horizontal force opposite to the direction of motion. The behavior of this force is determined by a frictional model. In a number of instances, virtual textured surfaces have been generated by varying horizontal forces alone, with no significant variations in vertical surface topology [9, 96]. Variations in horizontal forces can thus be perceived as roughness for a virtual surface. This has also been convincingly demonstrated for real surfaces where it was found that roughness correlated well with changes in forces tangential to the exploring finger and was reduced when friction decreased [126].

In this thesis, it has been shown that geometric variations in surface elevation affect the perception of texture roughness, even when lateral forces are largely excluded. There is a direct connection between the vertical motion of the probe in the z axis and the perceived roughness of a dithered texture. In this setting, the physical property which characterizes roughness best appears to be variability in the z -axis force signal. The addition of lateral friction forces to such a vertically-defined texture geometry is likely to create a more complex perception of roughness.

It is hypothesized that the presence of friction will confound the ability to discriminate between textures with varying surface geometries. Since the lateral forces generated by friction models can themselves be interpreted as texture, it is likely that higher levels of friction will result in higher reported subjective roughnesses even for those texture spacings at which subjects reported low

roughness for simple geometric textures. This effect will likely be most profound for stick-slip friction models, as these models result in rapidly varying lateral forces when a probe is moved across a surface. In contrast, viscous texture models should have little effect as they produce smooth changes in force, that vary only as subjects vary the speed of the probe on the surface.

8.2 Virtual Friction Models

Five friction models were initially examined for potential use in psychophysical experiments examining roughness perception. These models ranged from simple viscous friction to complicated stick-creep-slip-slide models. Since large scale human subject trials on all five models would have been prohibitively time consuming, it was considered important to choose two models which differed as much as possible from each other. This led to the ultimate selection of simple viscous friction and a sophisticated form of stick-slip friction first developed by Dupont, Armstrong and Hayward [30, 43] and based on Dahl's model [26] which exhibits both stiction and presliding displacement. Additional selection criteria included stability of the model, subjective realism, and the ease with which model parameters could be manipulated.

The following friction models were implemented and evaluated for subjective realism and ease of use.

- **Viscous friction model**

In this simplest of friction models, a force, proportional to probe velocity, opposes motion [103]. Thus

$$f(x) = -k\dot{x}. \quad (8.1)$$

The sensation to the user is that of moving through a fluid with the probe tip. Implementation of the model involves applying viscous forces only when the probe is in contact with the surface.

- **Karnopp friction model**

The Karnopp friction model is a stiction model in which force is proportional to velocity for a region along the velocity axis of $\pm d$ about zero velocity, and a constant, C , once velocity, $|d|$, is exceeded [61].

$$f(v) = \begin{cases} kv & \text{if } -dv < v < dv; \\ C & \text{otherwise.} \end{cases} \quad (8.2)$$

This model has previously been implemented on a magnetically levitated haptic device [116], a 3DOF planar twin pantograph mechanism [37] and on more specialized systems [111, 112]. The formulation uses the derivative of position as its input and it thus susceptible to significant noise at low velocities. Implementation of this model on the MLHD suffered no such noise effects, however, since the Karnopp model is simply a complicated variant of viscous friction and does not feel subjectively different from it, it was rejected in favor of the simpler viscous model.

- **Coulomb model**

This model is based on the virtual spring concept [4, 9]. When a real probe is at rest and begins to move, displacement of asperities between it and the surface occur elastically, until some point is reached beyond which plastic deformation happens and the device slides. To simulate this effect, a virtual spring is used to attach the tip of the virtual probe to its current location. The spring stretches for some distance and then releases, allowing the probe to slide with only viscous frictional forces continuing to impede motion. While sliding, the position of the spring is continually reset to the current location and, once tangential forces drop below some proportion of the applied normal force, it is used to again to cause sticking. This model provides a simple stick-slip sensation but suffers from chatter as the probe moves rapidly between sticking and sliding states during motion at critical velocities.

- **Hollerbach Model**

The Hollerbach model is also a stick-slip model based on the idea of a virtual spring [100]. When the probe is stuck, the frictional force, F , is determined from the normal force, $|n|$, and the distance, x , the probe is away from the virtual spring sticking point, c ,

$$F = k_f |n| (x - c). \quad (8.3)$$

where k_f is the constant of friction. The virtual sticking point, c , is found when sliding motion stops based on the position at that time, a , a dynamic coefficient of friction, μ_d , and the direction of the velocity vector, v :

$$c = a - \frac{\mu_d}{k_f} \frac{v}{|v|}. \quad (8.4)$$

The probe remains stuck until $F \geq \mu_s |n|$ (where μ_s is the static coefficient of friction) at which point sliding motion is initiated. Sliding motion occurs as long as the absolute value of velocity is less than an arbitrary value ($|v| \leq v_{min}$) and the force during this time is proportional to the normal force and the direction of velocity:

$$F = \mu_d |n| \frac{v}{|v|}. \quad (8.5)$$

This model suffers from the same problems as those of the simple stick-slip model, namely oscillations at certain movement speeds, although it provides a realistic stick-slip feel for slow motions.

- **Hayward Model**

The Hayward model is the most complicated model implemented and is capable of rendering stick, slip (in this case a condition in which relaxation oscillations occur as the probe tip rapidly and repeatedly slips and then slides short distances) and pure sliding motion [43]. It is also possible to simulate creep.

This model is also based on the idea of a virtual spring such that the force, F , is proportional to the stretch, s , in the spring where

$$F = -k_{Hay} s \quad (8.6)$$

and

$$s = x_k - w_k. \quad (8.7)$$

where w_k is found from

$$w_k = \begin{cases} x_k - \frac{x_k - w_{k-1}}{|x_k - w_{k-1}|} s_{max} & \text{if } \alpha(s)|x_k - w_{k-1}| > 1; \\ w_{k-1} + y_k \alpha(s)(x_k - w_{k-1}), & \text{otherwise.} \end{cases} \quad (8.8)$$

where $\alpha(s) = \alpha(x_k - w_{k-1})$ and $y_k = x_k - x_{k-1}$ and for the stick-slip-slide mode,

$$\alpha(s) = \begin{cases} 0 & \text{if } \|s\| \leq s_{stick}; \\ \frac{1}{s_{max}}, & \text{elsewhere} \end{cases} \quad (8.9)$$

If we instead choose $\alpha(s)$ to be a smooth function but similar in form to equation 8.9, for example by using

$$\alpha(s) = \frac{1}{s_{max}} \frac{s^8}{s_{stick}^8 + s^8}, \quad (8.10)$$

equation 8.8 produces friction which transitions smoothly from slipping to sliding. The model then exhibits stick-slip-creep-slide characteristics. The Hayward model subjectively yields the best results of the five models tested with a smooth stick-slip sensation whose parameters can be finely tuned. It is the most computationally expensive of the five models but this has not resulted in any instability or latency issues. Since the Hayward friction model was also the only stick-slip model investigated which did not suffer from instability or chatter, it was chosen for large scale psychophysical studies.

8.3 Friction and Roughness: Experimental Design

The Hayward and viscous friction models were used for psychophysical experiments. The models were applied to the constraint surface algorithm (CSA) used previously to generate dithered conical textures with spherical probes (see Chapter 5).

The Hayward model of friction involves a number of variables which can be manipulated. For simplicity, the k_{Hay} variable is chosen as a variable. Since the frictional force F is determined by $F = k_{Hay}z$, in which k_{Hay} can be considered as a spring constant multiplying the variable parameter z , it seems logical to set z 's determinants, Z_{max} and Z_{stick} , to constant values. These values determine the amount of stretch that is allowed in the virtual spring prior to its motion and

the degree to which the spring has a propensity to stick to its current location. The two variables together define the stick-slip characteristic of the texture while k_{Hay} simply scales the effect.

Four levels of k_{Hay} were used: 0.0, 0.5, 1.0 and 1.5 N/mm. These levels were subjectively distinguishable and realistic. None of them required subjects to apply large forces to move the MLHD manipulandum. Z_{max} and Z_{stick} were set at 1.4 and 2.0 mm respectively.

Two levels of viscosity were implemented: 0.04 N/mm/s and 0.06 N/mm/s. These levels of viscosity were chosen because they were subjectively distinguishable from each other and from the frictionless state but were not high enough to noticeably impede probe motion. Frictional force was applied only when the probe was in contact with a texture surface and opposed translational velocity but not rotation.

A spherical probe with a radius of 0.5 mm was used on a constraint surface consisting of dithered elements. The texture elements were truncated cones ($el_h = 0.42$ mm, $R_{top} = 0.23$ mm, $R_{base} = 0.52$ mm, $\alpha = 53^\circ$). The cones were dithered by up to 40% of their initial spacing with zero-mean white noise. The probe and texture elements remained the same for all levels and types of investigated textures.

A total of 6 levels of friction were therefore used in the experiment: 2 levels of viscosity and 4 levels of k_{Hay} . For each level of friction parameter, subjects explored 10 different element spacings ranging from 0.5-5.5 mm (See Appendix B, Section B.1.6 for a complete list of the texture spacings used). A trial consisted of the exploration of a single spacing-friction level combination. Each spacing-friction level combination was repeated 3 times. A total of 180 trials were therefore performed by each subject in the course of an experiment. The trials were presented in random fashion to prevent learning effects. Randomization also allowed absolute magnitude comparisons to be made between friction models since subjects presumably used the same scale to judge roughness for all trials.

A total of 17 subjects from Carnegie Mellon University's psychology department experimental subject pool took part in roughness magnitude estimation. Ten were female and 7 were male, Two subjects were left-handed but performed the experiment with their non-dominant (right) hand.

Subjects were seated approximately 500 mm from a graphical display used to enter the roughness estimates, with the MLHD on their right-hand side. The texture was only displayed haptically. White noise, played through headphones ensured that audio cues were not available to discriminate between textures.

Subjects were informed that they would encounter the textures as a series of trials. Trials were presented in two blocks: a demonstration block and an experimental block. The demonstration block consisted of 30 randomly ordered trials, in which five texture spacings, spanning the full range of 0.5-5.5 mm and including its extremes, were displayed, along with all 6 levels of the two types of friction. The demonstration block allowed subjects to develop an internal scaling system for the range of textures which they were about to encounter. After the demonstration block, actual magnitude estimation began. Subjects entered a numeric value using a computer keyboard and were informed of their progress by a reported trial number but otherwise received no other feedback on performance. Subjects were not instructed how to feel the texture and were given no restrictions on time. Although experiments were slated to run for one hour, most subjects finished in much shorter time frames.

Subjects were told that they could assign roughness estimates to any positive range of numbers but that larger numbers were to reflect larger values of roughness and smaller numbers were to represent smaller values of roughness. They were specifically asked not to use 0 or negative numbers.

For this experiment the MLHD proportional gains were set to nominal values of 10 N/mm in translation and 25 Nm/radian for orientation. This provided a relatively stiff surface and prevented, to a large extent, rotation of the manipulandum. Derivative gains for the MLHD were set to 0.04 N/mm/s in translation and 0.5 N/radian/s for orientation to prevent instability. A feedforward force reduced the weight of the flotor to approximately 70 grams.

8.4 Friction effects on Roughness Perception

Subjects in all previous experiments in this thesis experienced forces which only varied in the vertical direction, along the z axis. The textures which they experienced were effectively frictionless. Since the MLHD manipulandum was constrained to remain aligned with the z axis, subjects should not have experienced any torque unless they attempted to twist the manipulandum against the constraint. Such torques should have little or no effect on the magnitude of perceived roughness since they were not generated by surface contacts but rather, by attempted changes in manipulandum angle introduced by the subject themselves.

Overlaying a texture model on the geometric surface generated by the CSA, introduces a variable force in the horizontal plane. Z -axis forces, from the interaction between probe and texture

geometry, still exist, but x -axis and y -axis forces now become part of the subjective experience of roughness.

The frictional forces will generally be much smaller than the forces generated by the surface. For stick-slip friction, they will vary rapidly with probe motion, as it sticks and slides across the surface. For viscous friction, they vary smoothly with changes in probe velocity. If, as previous experiments indicate, the physical property experienced as roughness is force variability, as measured by the total power in the force signal, then these two kinds of friction should have very different effects on the psychophysical function for roughness, $\Psi(I)$.

Stick-slip friction, which, in this experiment is modeled using Hayward's technique, will increase the total variability in the force signal. Assuming, for the moment, that the direction of the force vector on the fingerpads is not significant, this should have the effect of increasing the roughness reported by subjects, when geometrically identical textures are explored. It is, of course, possible that the direction of the applied force changes the sensation of roughness as studies have shown that different regions of the fingerpad are more or less sensitive to deformation and stretch and the direction of stretch may be important in perceived force [40, 106]. Certainly, changes in tangential force have been associated with the perception of roughness in previous studies [9, 126]. The role of changes in normal force with respect to roughness perception has not been well defined.

Since subjects' grips on the cylindrical manipulandum are not controlled it is difficult to determine which axis of motion is tangential and which is normal to their fingerpads. Since results are averaged over subjects and trials, all forces will be considered to be tangential and contributing to roughness perception.

Since the frictional forces are generally smaller than the forces generated by the surface, it is expected that changes in roughness perception, resulting from frictional forces, will be most notable when forces related to probe-texture geometry are minimal. When a spherical probe is used to explore dithered conical textures, this should occur at very small and very large element spacings, far from the drop point (DP). At these locations, the probe is either riding on top of tightly packed elements or sliding along the texture surface between sparsely spaced elements.

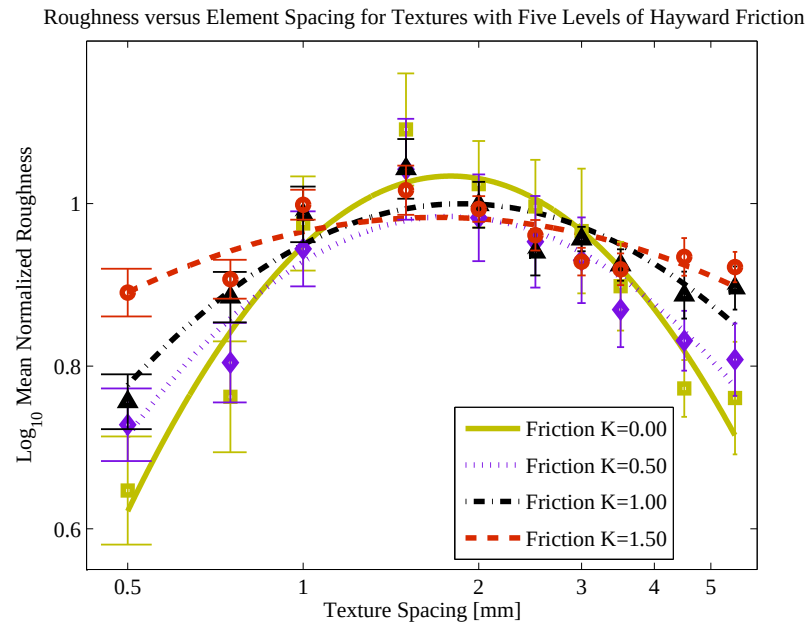


Figure 8.1: Second order fit to mean normalized roughness versus texture spacing for four levels of stick-slip friction (Hayward model).

k_{Hay} [N/mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.00	-1.34	1.31	1.79	1.74
0.50	-0.88	1.56	1.79	1.66
1.00	-0.68	2.06	1.87	1.43
1.50	-0.33	2.56	1.70	1.31

Table 8.1: The maxima of roughness functions based on 2nd and 3rd order fits to magnitude estimation data for four levels of the Hayward friction model's k_{Hay} . Curvature and the predicted maxima of the 2nd order fitted curve on the log-log plot are also shown.

Figure 8.1 shows roughness magnitude estimates when four levels of Hayward friction are applied to a set of dithered conical texture surfaces explored with a 0.5 spherical probe. The level of friction, as measured by the friction parameter k_{Hay} , ranges from 0 to 1.5 N/mm. This parameter scales the total force output from Hayward’s model, thus a value of 0 corresponds to no frictional force. The figure shows that with no friction, $\Psi(I)$ assumes its characteristic inverted “U”-shaped curve, with an R^2 value for a quadratic fit of 0.91 (see Appendix A, Table A.30). The element spacing of maximum roughness, seen in Table 8.1, is 1.79 mm. This is very close to the maximum of 1.93 mm found for a 0.5 mm spherical probe during the friction-less probe size experiments in Chapter 5. The DP predicted by the geometric model, for a 0.5 mm spherical probe on dithered conical textures, is 1.56 mm. The DP predicted by the geometric model, revised for the determined mean planar probe velocity (with no friction) of 46.6 mm/sec is 1.99 mm. The value of 1.79 mm is therefore quite close to both the predicted and previously determined values.

Factor	DOF	F	p-value
Curvature	3/64	4.99	< 0.01
Curve Height	3/64	0.56	> 0.05
2nd Order Maxima	3/64	1.97	> 0.05
3rd Order Maxima	3/64	1.20	> 0.05

Table 8.2: Significance of stick-slip friction effects, determined using a 1-way ANOVA, on curvature, curve height and maxima of a 2nd and 3rd order fit to roughness magnitude estimates.

As stick-slip friction increases, the DP remains essentially unchanged, as does the maximum height of $\Psi(I)$. However, the absolute curvature of $\Psi(I)$ decreases with increasing levels of friction. A 1-way ANOVA shows that friction significantly affects curvature but has no effect on the DP or the maximum height of $\Psi(I)$. This decrease in curvature is a result of the increased roughness experienced by subjects when the probe is passing over either very small spacings or very large spacings. Clearly, the effects of friction on roughness are most substantial where the effects of geometry are smallest.

The increase in roughness at the extremes of the element spacing range result in an almost linear $\Psi(I)$ for the highest friction level. That even the small tangential forces due to friction can cause smooth surfaces to feel as rough as the roughest textures without friction suggests several possibilities. First, it is possible that the tangential forces generated by the friction model are somehow

registered as more significant than those generated by probe-texture geometry. It is possible that changes in force that are unassociated with changes in position are considered more significant by higher level neural processing. It is also possible that, for some level of force signal power, saturation of the sensation of roughness is reached. Thus maximum roughness at the DP is unchanged but minimum roughness is increased. Whatever the reason, it is clear that stick-slip frictional effects interfere with purely geometric effects with respect to roughness perception. While friction has little effect on the maximum roughness experienced or the location of that maximum, a large amount of stick-slip friction will tend to overwhelm smaller geometric effects, leveling the roughness at some high value.

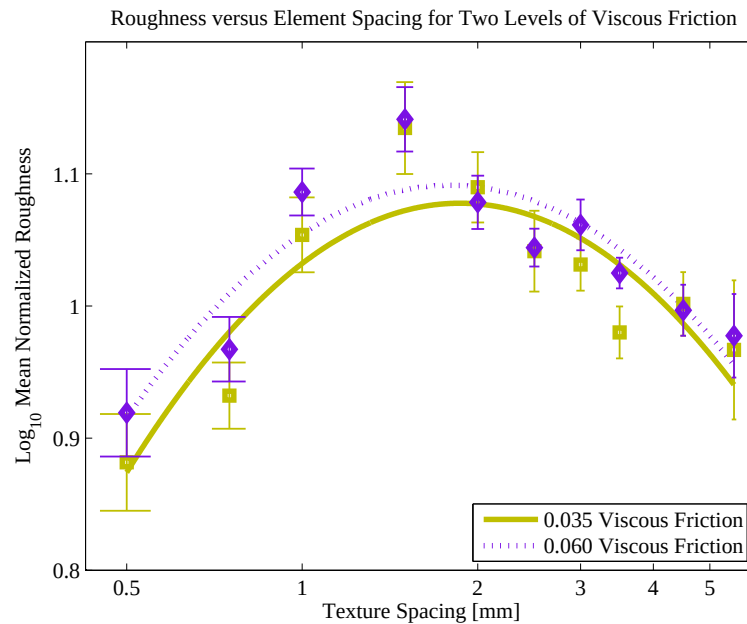


Figure 8.2: Second order fit to mean normalized roughness versus texture spacing for two levels of viscous friction.

The effects of viscous friction on roughness can be seen in Figure 8.2 and Table 8.3. As with stick-slip friction, the DP does not change significantly with the level of friction (see Table 8.4 for a 1-way ANOVA of the effects of viscous friction). It is very close to the value of the DP for identical textures and a 0.5 mm probe (1.93 mm) and not far from the velocity-revised geometric model predictions of 2.09 mm for a mean planar velocity 57.5 mm/sec.

In contrast to stick-slip friction, however, the absolute curvature of $\Psi(I)$ is also unchanged. Since the variability of force is the physics property which appears to characterize roughness, this finding is not surprising. Viscous friction will certainly not increase force variability. In fact, since

k_b [N/mm/sec]	2nd Order Curv.	2nd Order Max. [mm]	3rd Order Max [mm]
0.04	-0.62	1.87	1.59
0.06	-0.57	1.79	1.55

Table 8.3: The maxima of the dithered conical texture roughness functions based on 2nd and 3rd order curves in a log-log plot. Curvature of the 2nd order fitted curve on a log-log plot of roughness versus spacing is shown. Results are shown for two levels of viscous friction.

it is a damping force, it will tend to decrease motion variability, presumably decreasing the power in the force signal at the same time. When force signal power is examined in Section 8.5 below, it unfortunately does not show the expected significant decrease with increasing friction. This may be due to the very low levels of viscous friction studied. It is interesting to note that the mean planar velocity for the viscous friction experiment is actually slightly larger than that of the experiments in Chapter 5 in which no frictional forces were used. This suggests that subjects either compensate for the viscous forces and maintain or increase probe velocity, or the level of force is insignificant enough to leave motion unaffected. If the latter point is true, then the amount of viscous friction used here is unlikely to have had a significant effect on force variability either.

Factor	DOF	F	p-value
Curvature	1/32	0.06	> 0.05
Curve Height	1/32	1.12	> 0.05
2nd Order Maxima	1/32	2.85	> 0.05
3rd Order Maxima	1/32	0.99	> 0.05

Table 8.4: Significance of probe size effects in viscous friction experiment, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to roughness magnitude estimates.

8.5 Friction and the Physics of Roughness

In all previous experiments in this thesis, the physical property which best characterizes roughness is found to be force variability, as measured by the total power in a PSD periodogram of the z -axis force signal. Correlation between the physical function for total z -axis force signal power, $\Phi(I)$, with the psychophysical function for roughness, $\Psi(I)$, is high for point-probes, spherical and conical probes

and a variety of texture geometries including sinusoidal and trapezoidal gratings as well as dithered conical gratings. Correlation between $\Phi(I)$ and $\Psi(I)$ even remains high when increased compliance substantially reduces texture roughness.

	$k_{Hay} = 0.0$ N/mm		$k_{Hay} = 0.5$ N/mm		$k_{Hay} = 1.0$ N/mm		$k_{Hay} = 1.5$ N/mm	
Parameter	Corr. C.	p	Corr. C.	p	Corr. C.	p	Corr. C.	p
Mean Position	0.12	> 0.05	-0.25	> 0.05	0.07	> 0.05	-0.03	> 0.05
Velocity	0.98	< 0.0001	0.99	< 0.0001	0.96	< 0.0001	0.89	< 0.001
Acceleration	0.99	< 0.0001	0.98	< 0.0001	0.97	< 0.0001	0.93	< 0.0005
Energy	0.96	< 0.0001	0.96	< 0.0001	0.92	< 0.0005	0.88	< 0.001
Position Std	0.87	< 0.005	0.89	< 0.001	0.80	< 0.01	0.60	> 0.05
Mean Force	0.03	> 0.05	-0.19	> 0.05	-0.37	> 0.05	0.13	> 0.05
Max Power	0.85	< 0.005	0.69	< 0.05	0.85	< 0.005	0.86	< 0.005
Freq. Max Pow.	0.90	< 0.0005	0.94	< 0.0001	0.89	< 0.001	0.84	< 0.005
FA1 Power	0.95	< 0.0001	0.98	< 0.0001	0.92	< 0.0005	0.86	< 0.005
FA2 Power	0.96	< 0.0001	0.95	< 0.0001	0.95	< 0.0001	0.92	< 0.0005
Total Power	0.97	< 0.0001	0.98	< 0.0001	0.93	< 0.0001	0.87	< 0.005

Table 8.5: Correlation coefficients for various physical properties when compared to the roughness function, for dithered conical textures with varying levels of Hayward friction. Outliers have been removed from maglev and subject data.

It is therefore interesting to observe that, as stick-slip friction increases, the z -axis force signal's total power $\Phi(I)$, begins to lose its correlation with the roughness function (see Table 8.5). Figure 8.3 shows that the force signal's $\Phi(I)$ retains its “U”-shaped form as friction increases. The mean location of the $\Phi(I)$ maxima (see Table 8.6) is unchanged with friction at an element spacing of 1.87 ± 0.04 mm, close to the mean value of 1.79 ± 0.04 mm found for the roughness function maxima. The mean curvature of the $\Phi(I)$ s for total power is -1.67 ± 0.08 mm while the curvature for roughness when no friction is applied is -1.34 mm. None of the changes in the $\Phi(I)$ for total power in the z -axis force signal are significantly affected by changes in k_{Hay} (see Table 8.7). $\Phi(I)$'s shape thus continues to closely resemble that of the frictionless roughness function, in spite of increasing friction levels.

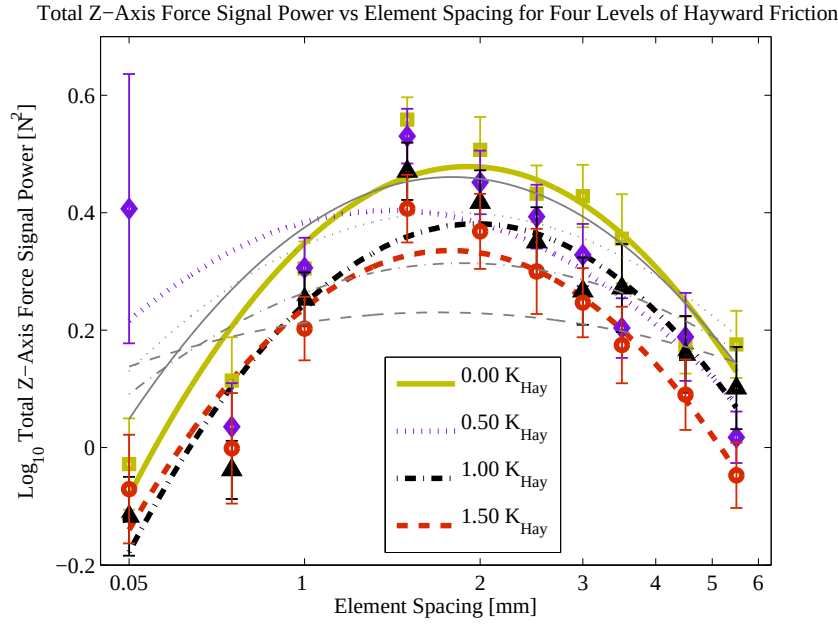


Figure 8.3: Second order fit in a log-log plot to total power in the z -axis force signal plotted against texture spacing for four levels of stick-slip friction (Hayward model). Subject roughness estimates, normalized to power, are shown as thin gray lines for comparison.

k_{Hay} [N/mm]	2nd Order Curv.	2nd Order Max. [mm]	3rd Order Max [mm]
0.00	-1.66	1.91	2.00
0.50	-1.89	1.83	1.86
1.00	-1.58	1.97	2.00
1.50	-1.56	1.78	2.00

Table 8.6: The maxima of 2nd and 3rd order fits to the total power in the z -axis force signal functions in a log-log plot for four levels of the Hayward friction k_{Hay} . Curvature of the 2nd order fitted curve is also shown.

The roughness function, on the other hand, flattens out with increasing friction, approaching the form of a straight line at maximum roughness. The reason for this flattening of $\Psi(I)$ has already been discussed above (Section 8.4) and is thought to relate to the fact that subjects do not discriminate between the planar stick-slip force variations and those generated by changes in the vertical topography by the CSA; both sets of forces are felt as roughness. When the vertical topology dictates low z -axis forces, the lateral forces due to friction are still felt as roughness. The fact that z -axis force variability can be fit by a second order equation (see Appendix A, Table A.32), which

Factor	DOF	F	p-value
Curvature	3/64	0.87	> 0.05
Curve Height	3/64	0.79	> 0.05
2nd Order Maxima	3/64	1.01	> 0.05
3rd Order Maxima	3/64	0.08	> 0.05

Table 8.7: Significance of Hayward friction effects, determined using a 1-way ANOVA on curvature, height, and maxima of 2nd and 3rd order fits to total power in the z -axis force signal.

matches the zero-friction roughness function quite well but retains this form, even as roughness degrades from the quadratic, is evidence that stick-slip friction is adding noise to the geometrically-generated forces which, until now, have characterized friction in this thesis.

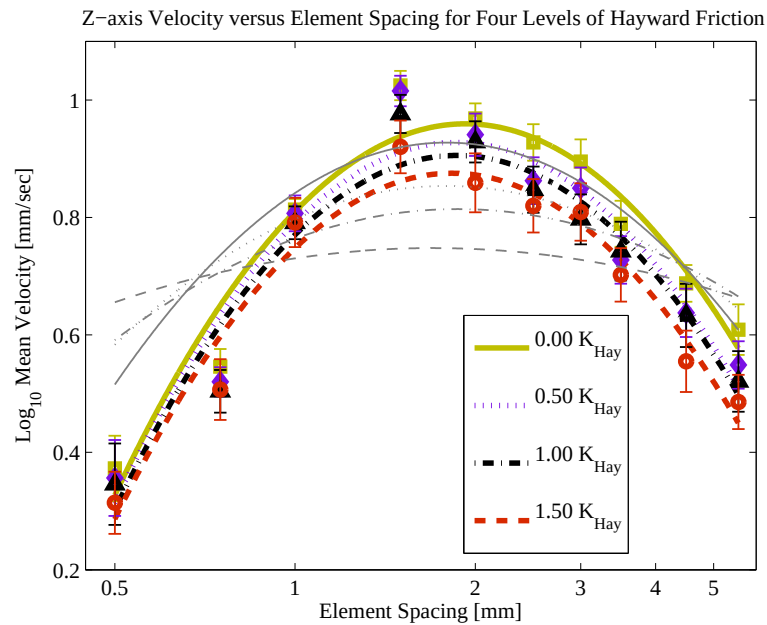


Figure 8.4: Second order fit to mean absolute instantaneous z -axis velocity of the haptic probe versus texture spacing for four levels of stick-slip friction (Hayward model). Subject roughness estimates, normalized to velocity, are shown as thin gray lines for comparison.

The correlation between total power in the z -axis force signal and the frictionless roughness functions gives further evidence that force variability is the physics function which characterizes roughness. This is further supported by the observation of the predicted decline in correlation which results from the introduction of unmeasured horizontal forces from stick-slip friction.

Most other physical properties, which previously had correlated well with roughness, show similar effects, with good correlation for low levels of stick-slip friction and poorer correlation for high levels (see Table 8.5). This includes mean absolute instantaneous z -axis velocity, acceleration and kinetic energy as well as the power in the force signal bandwidths associated with the FA1 and FA2 receptors (5-50 and 50-500 Hz respectively).

k_{Hay} [N/mm]	2nd Order Curv.	2nd Order Max. [mm]	3rd Order Max [mm]
0.00	-1.84	1.93	1.95
0.50	-1.88	1.86	1.86
1.00	-1.85	1.86	1.86
1.50	-1.86	1.83	1.82

Table 8.8: The maxima of z -axis velocity functions based on 2nd and 3rd order fits to z -axis velocity in a log-log plot. Curvature of the 2nd order fitted curve is also shown. Results are shown for four levels of the Hayward friction model's k_{Hay} .

The velocity $\Phi(I)$ (see Figure 8.4), for example, has no significant change in its curvature, the location of its maxima, or the height of its maxima which can be said to result from stick-slip friction (Table 8.9). Its mean DP is 1.87 mm, which is very close to the mean DP for $\Psi(I)$. Its mean curvature is -1.85 mm which is larger than the mean curvature of -1.67 for total power and still larger than the curvature of -1.34 mm found for the frictionless $\Psi(I)$. This larger curvature suggests that, while velocity and total power both seem to characterize roughness, they do not do so in an identical fashion.

Factor	DOF	F	p-value
Curvature	3/64	0.28	> 0.05
Curve Height	3/64	1.65	> 0.05
2nd Order Maxima	3/64	0.39	> 0.05
3rd Order Maxima	3/64	0.55	> 0.05

Table 8.9: Significance of Hayward friction effects, determined using a 1-way ANOVA on curvature, height and maxima of 2nd and 3rd order fits to z -axis velocity.

Viscous friction, since it should have a damping effect on motion, is expected to decrease force variability and thus diminish the total power in the z -axis force signal. This should have no effect on

the roughness $\Psi(I)$ other than to decrease it at all element spacings. The total power in the z -axis force signal can be seen in Figure 8.5.

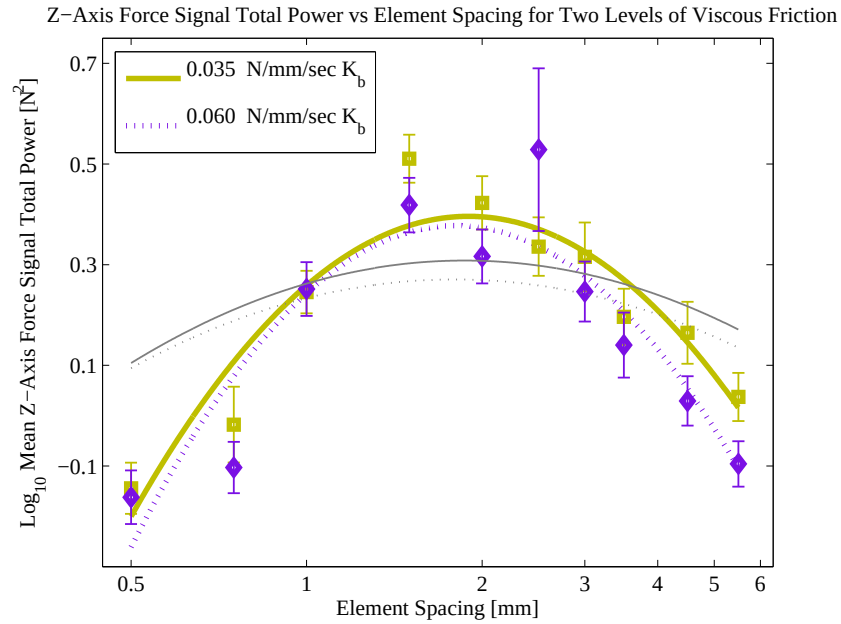


Figure 8.5: Second order fit to total power in the z -axis force signal versus texture spacing for two levels of viscous friction. Subject roughness estimates, normalized to power, are shown as thin gray lines for comparison

Probe k_f [N/mm/s]	2nd Order Curv.	2nd Order Max. [mm]	3rd Order Max [mm]
0.04	-1.78	1.90	1.93
0.06	-1.81	1.79	1.87

Table 8.10: The maxima of 2nd and 3rd order fits to total power in the z -axis force signal versus element spacing data for two levels of viscous friction. Curvature of the 2nd order fit is also shown.

The DP for total power shows little change with levels of friction and is very close to the DP for frictionless textures (Table 8.10). It is interesting to note that $\Phi(I)$ for total power does not diminish significantly (see Table 8.11) for increasing viscous friction but it appears to differ somewhat from roughness, having a higher curvature. This effect is not unlike that seen for stick-slip friction in which the smallest and largest element spacings showed the most significant differences between roughness and force variability. At the extremes of element spacings roughness is higher than

would be expected purely from z -axis force variability even though correlation between the two is still high.

Factor	DOF	F	p-value
Curvature	1/32	0.01	> 0.05
Curve Height	1/32	0.54	> 0.05
2nd Order Maxima	1/32	1.28	> 0.05
3rd Order Maxima	1/32	0.31	> 0.05

Table 8.11: Significance of viscous friction effects determined using a 1-way ANOVA on curvature, height and maxima of 2nd and 3rd order fits to the total power in the z -axis force signal.

The difference between power and roughness functions when viscous friction is applied, must be related to the effects of the friction in the lateral axis. Since viscous friction should not increase lateral force variability it must act in some other way to produce the observed changes. Possibly, changes in speed, or simply the force needed to overcome viscosity, somehow make it difficult for subjects to discriminate texture based on roughness. If higher overall z -axis forces are applied by subjects when viscous friction is present, the power in the force signal might increase, making discrimination between levels of roughness more difficult. Whatever the reason, viscous friction must be seen as a confounding factor when it comes to roughness perception.

Probe k_f [N/mm/s]	2nd Order Curv.	2nd Order Max. [mm]	3rd Order Max [mm]
0.04	-2.04	1.89	1.81
0.06	-1.81	1.85	1.86

Table 8.12: The maxima of 2nd and 3rd order fits to the the mean z -axis velocity data in a log-log plot for two levels of viscous friction. Curvature of the 2nd order fit is also shown.

It is noted that the z -axis velocity function also fails to reflect the shape of the roughness function when viscous friction is applied (Figure 8.6). While the correlation coefficients for both velocity and total power in the z -axis force signal are high (Table 8.14), they fail to take into account the increase in roughness seen at the extremes of element spacing when viscous friction is present.

For both viscous and stick-slip friction, the correlation coefficient between roughness and power is high in both the FA1 and FA2 bandwidths of the z -axis force signal. Thus, this experiment

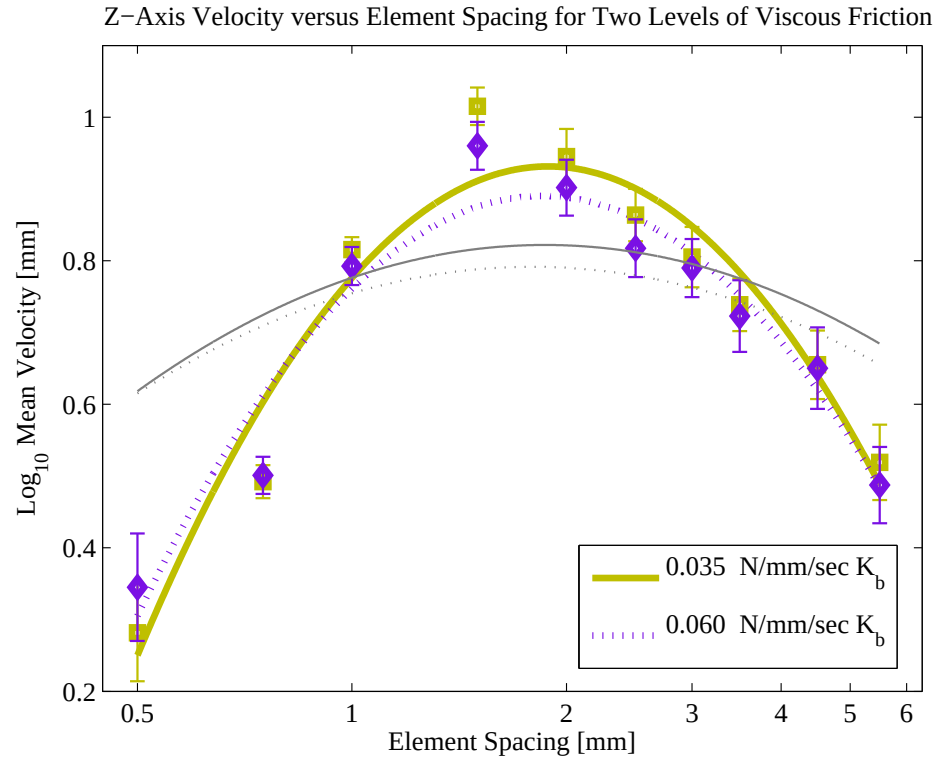


Figure 8.6: Second order fit to mean z -axis velocity plotted against texture spacing in a log-log plot for two levels of viscous friction. Subject roughness estimates, normalized to velocity, are shown as thin gray lines for comparison

Factor	DOF	F	p-value
Curvature	1/32	0.73	> 0.05
Curve Height	1/32	0.87	> 0.05
2nd Order Maxima	1/32	0.12	> 0.05
2nd Order Maxima	1/32	0.44	> 0.05

Table 8.13: Significance of viscous friction effects on the curvature, height and maxima of the 2nd and 3rd order fits to z -axis velocity, determined using a 1-way ANOVA.

also fails to determine which of the two receptors is most important in sensing texture roughness.

	$k_f = 0.04$ N/mm/s		$k_f = 0.06$ N/mm/s	
Parameter	Corr. C.	p	Corr. C.	p
Mean Position	-0.04	> 0.05	-0.14	> 0.05
Velocity	0.98	< 0.0001	0.94	< 0.0001
Acceleration	0.98	< 0.0001	0.95	< 0.0001
Energy	0.96	< 0.0001	0.90	< 0.0005
Position Std	0.96	< 0.0001	0.51	> 0.05
Mean Force	-0.23	> 0.05	0.43	> 0.05
Max Power	0.90	< 0.0005	0.71	< 0.05
Freq. Max Pow.	0.92	< 0.0005	0.90	< 0.0005
FA1 Power	0.96	< 0.0001	0.95	< 0.0001
FA2 Power	0.97	< 0.0001	0.93	< 0.0005
Total Power	0.96	< 0.0001	0.95	< 0.0001

Table 8.14: Correlation coefficients for various physics properties when compared to the roughness psychophysical function for dithered conical texture with varying levels of viscous friction. Outliers have been removed from maglev and subject data.

8.6 Conclusions

Friction, which impedes motion in the lateral direction, can be seen as a confounding factor in the perception of roughness. Stick-slip friction, in particular, results in rapidly varying forces in the plane which, in previous studies [9, 96, 126], have been associated with the sensation of roughness. Viscous friction, too, appears to interfere with the perception of roughness.

Roughness, with increasing stick-slip friction, retains its inverted “U”-shaped psychophysical function, however, as frictional levels increase, the function “flattens out” and begins to approach a straight line. In contrast to the effect of increasing compliance, however, the linear function approached with high levels of friction is near the maximum level of roughness, rather than the minimum. The roughness levels at the extremes of element spacing are increased while levels near the DP are roughly unchanged.

The reason for this behavior is not completely apparent, although it seems that the effects of probe-texture geometry on roughness are most significant at the DP while the effects of friction are most significant when the topology of the surface is nearly smooth. If the lateral forces of stick-slip

friction are small but relatively constant in their variability, this might be the expected effect. The measured z -axis velocity and force physical functions do not show any significant changes in form with increasing levels of stick-slip friction and match the profile of the zero-friction psychophysical roughness function well. Clearly the motion or forces generating perceived roughness are not measured purely in the z axis, even though probe-texture geometry still appears to control the location of the DP and the overall form of the roughness function.

Changes in the level of viscous friction appear to have little effect on the roughness function, either in shape or level of intensity. This may be because the levels of viscous friction chosen for this experiment were insufficient to produce statistically significant changes or, perhaps, viscous friction has little effect compared to geometric considerations.

Interestingly, the most closely examined physical properties, namely z -axis force signal power and velocity $\Phi(I)$ s, while correlating with roughness and having the same DP, were considerably more curved and failed to capture the exact shape of the roughness function. The reason for this is unclear. It is possible that the horizontal forces of viscous friction are somehow reducing subjects' ability to feel z -axis force variability, possibly by a reduction in velocity, and this accounts for the discrepancy between the roughness and physical functions. However, this reduction in ability must be highly uniform in nature and does not alter the overall shape of the roughness function, beyond reducing its curvature.

Clearly friction complicates roughness perception in interesting ways which could benefit from further study. The contrast between geometric and pure force effects is an area which could be further investigated. Another area of interest is the difference between tangential and normal forces on the fingerpad and how these factor into the sensation of roughness: are they equivalent, and if not, how are they weighted with respect to the overall sensation of roughness.

Chapter 9

Conclusions and Contributions

When virtual textures are simulated using variations in surface geometry, it is important to consider how the geometry of the probe interacts with that of the surface. This thesis finds that roughness perception is clearly dependent on the size, shape and compliance of the exploring probe. When probe size, shape and compliance are simulated accurately, the perception of roughness in virtual textures is demonstrated to be nearly identical to that of corresponding real textures. This finding supports the role of haptic devices in the performance of psychophysical experiments, so long as proper consideration is given to hardware limitations and algorithmic geometric verisimilitude.

9.1 Roughness Perception with Virtual Probes

9.1.1 Roughness and Probe Size

One of the motivating factors for this thesis was the finding, by some researchers, that roughness perception appeared to be different for virtual and real textures [68, 91, 107]. Kornbrott *et al.* found that the virtual texture psychophysical function for roughness, $\Psi(I)$, was linear and varied substantially between subjects [68]. They hypothesized that the analytic combination of highly variable subject responses, with subjects having both negatively and positively sloped $\Psi(I)$ s, produced the inverted “U”-shaped function seen by Klatzky *et al.* in her studies of real texture [66].

Noting that Kornbrott’s group used a virtual point-probe on sinusoidal grating textures for their experiments while Klatzky’s studies used a dithered conical texture and a spherical probe, this thesis hypothesizes that the difference in their findings is related to differences in probe-texture geometry rather than some inherent difference between virtual and real textures, or differences in analysis.

In this thesis, Chapter 3 explores the use of a point-probe on sinusoidal grating textures using the MLHD in a manner similar to Kornbrott *et al.*'s studies [68]. This provides a baseline against which to compare her previous studies of virtual texture. It also provides material against which the later experiments in this thesis, which use a probe that has size, shape and compliance, can be compared.

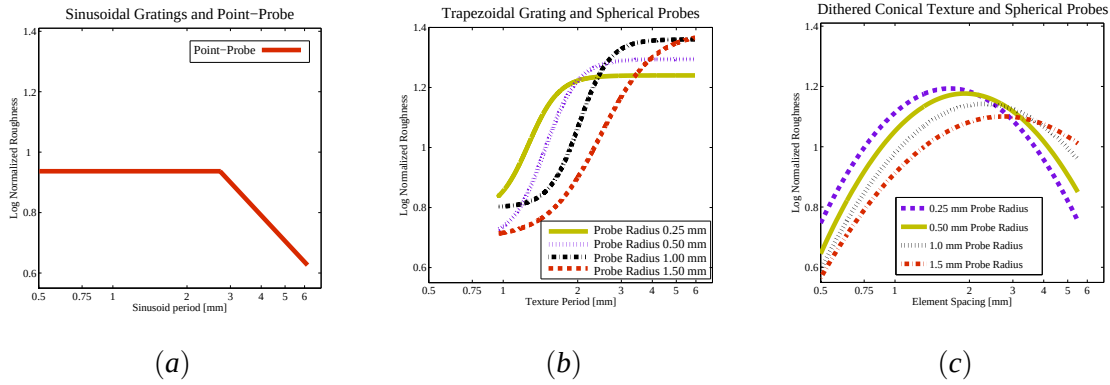


Figure 9.1: Comparison of the psychophysical function for roughness, $\Psi(I)$, for a) Sinusoidal gratings explored with a point probe. b) Trapezoidal gratings explored with spherical probes. c) Dithered conical textures explored with spherical probes.

The psychophysical function for roughness for a point-probe on sinusoidal gratings is found, in this thesis, to be neither linear nor “U”-shaped. Instead it consists of a long initial plateau of high roughness, followed by a linear decline in roughness, as element spacing increases beyond 2 mm (see Figure 9.1a). The slope of the declining portion of $\Psi(I)$ is -0.82, virtually identical to that found by Kornbrott *et al.* in their work. While some variation between subjects was observed in this study, the standard error of the slope is only 0.13. It seems clear that, for a point-probe on sinusoidal gratings, a linear $\Psi(I)$ is produced for element spacings larger than 2.0 mm.

It should be noted that the position bandwidth and maximum compliance of the haptic device used to generate textures may affect these results. Since the MLHD has a position bandwidth of approximately 120 Hz, a probe speed of 30-60 mm/sec, which is typical of the subjects in this thesis, will significantly attenuate the motion of the probe for spacings smaller than 0.2 mm. The PHANTOMTM device, used by Kornbrott's group, with its position bandwidth of 50 Hz [19], will not produce reliable textures for spacings smaller than approximately 0.5 mm. A second hardware issue related to the use of the PHANTOMTM device is its maximum stiffness of approximately 2

N/mm. Such a low stiffness (high compliance) results in a $\Psi(I)$ which is very low, nearly linear and highly variable, as seen in Section 7.4, Figure 7.1. This suggests that the inter-subject variability in $\Psi(I)$, seen by Kornbrott, may be related more to hardware limitations than to differences in individuals' perceptual processes.

Clearly, a virtual point-probe on a sinusoidal grating does not produce a psychophysical function for roughness which is the same as that observed with spherical probes on real dithered conical surfaces. Chapter 4 of this thesis, in which spherical probes interact with trapezoidal gratings, demonstrates that adding size to the probe substantially changes $\Psi(I)$ and that probe size affects the psychophysical function in a predictable way.

When trapezoidal gratings are explored with spherical probes, a constraint surface algorithm (CSA) is used to generate the path which the spherical probe's center will follow. The algorithm is based on the geometry of the probe-texture interaction. When the $\Psi(I)$ is found for each of several probe sizes, the shape of the function is still not the quadratic seen in Klatzky's real texture studies, but instead appears to be best fit by a logistic function (see Figure 9.1b). It is clear from Figure 9.1 that changing from a point-probe to a spherical one significantly alters $\Psi(I)$. The trapezoidal grating experiment also demonstrates that changing the size of the spherical probe will affect $\Psi(I)$, shifting the onset of maximum roughness to larger elements spacings.

The introduction of spherical probes does not cause $\Psi(I)$ to become the quadratic function seen by Klatzky for real textures. However, the onset of maximum roughness for trapezoidal gratings can be considered to be equivalent to Klatzky's *drop points* (DPs) and are predicted by her geometric model with moderate accuracy (see Table 4.1 in Section 4.4).

It is noted that the geometric model consistently underestimates the onset of maximum roughness. This is likely due to its quasistatic nature and a simple dynamics modification, which takes into account the velocity of the probe tip across the surface, improves consistency between the model and the experimental DP data (see Section 4.4, Figure 4.9). While the DPs, even with the revised model, still do not match experimental findings perfectly for trapezoidal gratings, the trend of increasing DP with increasing probe radius is significant by statistical measurement.

When the CSA is used to model the interaction of a spherical probe with dithered conical textures, the resulting $\Psi(I)$ matches real texture data to a high degree of accuracy. The virtual drop point, in particular, is nearly identical to the real drop points for matching probe radii. The trend of increasing DP with increasing probe size, seen with real textures, is also present. The curvatures of the virtual $\Psi(I)$ s, while not identical to those of real textures, are very close and decrease with

increasing probe size. This tendency of curvature to decrease with increasing probe size is also present, although not consistent, in the Klatzky experiments [66]. These findings indicate that it is possible to produce virtual textures which are nearly indistinguishable from real textures along the perceptual axis of roughness if the interaction between probe and texture geometry is carefully modelled.

The decrease in $\Psi(I)$ curvature and apparent decrease in $\Psi(I)$ height seen with increased probe size can be related to the path the probe follows as it traverses the constraint surface. For spherical probes, the radius of the arc of motion that occurs while crossing an element lip is related to the radius of the probe itself. A larger probe will therefore follow a path with more gradual changes in z -axis motion and forces, than will a smaller one (see Section 5.2. Figure 5.3). This results in a lower maximum roughness for larger probes as the physical property experienced as roughness is related to the rate of change in position or force and not just the absolute magnitude of the change. More gradual changes in motion and force also necessitate larger element spacings to induce significant changes in roughness. This effectively lowers subjective sensitivity to changes in element spacing, reducing $\Psi(I)$'s curvature.

Differences in $\Psi(I)$ between the trapezoidal grating and dithered conical textures are likely attributable to the regularity of the former. When a regular grating is crossed by a spherical probe, roughness increases with increasing penetration depth, as predicted by Klatzky's geometric model. Maximum penetration produces maximum roughness at roughly the predicted DP. The same factors govern roughness for dithered conical textures. However, once maximum penetration has occurred, the conical elements spread out, leaving the possibility that the probe may travel between them, or over their shoulders, without being forced to traverse their full height. With a grating, the probe must still pass over the full height of each element. Thus roughness remains high for grating textures even after the DP is reached, while for dithered cones, it diminishes.

9.1.2 Roughness and Probe Shape

An advantage of using a virtual texture to investigate texture perception is the ease with which experiment parameters may be manipulated. With simple modifications of the CSA it is possible to study the effects of a simple change in probe shape. When a cone-shaped probe is used to explore a dithered conical texture, it becomes clear that even a small change in probe shape changes its interaction with texture geometry, inducing changes in the form of $\Psi(I)$.

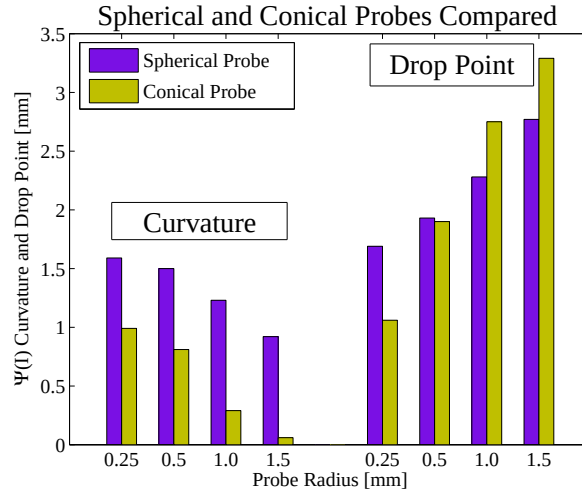


Figure 9.2: Comparison between spherical and conical probes of the curvature of a second order fit to the psychophysical roughness function for four probe radii on dithered conical textures. Also shown is the location of maximum roughness in terms of element spacing (the drop point) for spherical (2nd order fit) and conical (3rd order fit) probes.

The trend of decreasing curvature with increasing probe size is seen for both spherical and conical probe shapes. The conical probe, however, shows a significantly lower amount of curvature in $\Psi(I)$ than its spherical equivalent for all probe radii (see Figure 9.2). Spherical probes are thus more sensitive than conical ones to changes in element spacing. This finding may be due to the greater amount of noise generated by sharp transitions in the probe path which occur with conical probes. This noise, from abrupt changes in motion or force, may make roughness levels at different element spacings difficult for subjects to distinguish.

Conical probes show drop points which are similar to those of spherical probes. Both conical and spherical probes show the expected trend of increasing drop point with increasing radius. This is predicted by the geometric model. Since the geometric model equations are modified when the probe shape is modeled as a cone, it is not unexpected that the location of the drop point increases more rapidly with probe size for conical probes than it does for spherical ones.

Clearly, the modification of a probe's shape will influence the subjective perception of roughness as probe and texture geometry change the motion and forces experienced by a subject. Further studies with symmetric and asymmetric probe shapes might assist in determining the optimal shape for a probe which would maximize sensitivity and produce realistic texture perception.

9.1.3 Confounding Factors in Roughness Perception: Compliance and Friction

The ability to feel subtle changes in surface geometry is influenced by compliance [145]. The experiments of Chapter 7 demonstrate that changing compliance also affects the perception of roughness. These experiments clearly show that stiffer surfaces are perceived as rougher, for identical probe-texture geometries. This effect is most significant where roughness is maximal, at the DP, and least significant where surfaces are perceptually the smoothest. Stiffness appears to amplify the effects of geometry. This is potentially due to the larger range of forces experienced with stiffer surfaces. It may also be related to the ratio between the force on the probe created by texture geometry and the force created by the plane on which the texture elements sit.

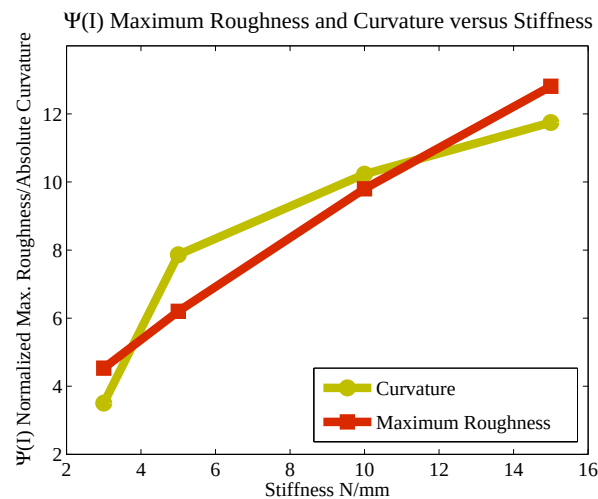


Figure 9.3: Maximum roughness and absolute curvature of a second order fit to roughness estimates for varying levels of compliance. Curvature is normalized to roughness for display purposes.

A significant conclusion from the results of compliance experiments is that, in order to effectively simulate the roughness of a relatively stiff surface, such as wood or metal, a haptic device capable of stiffnesses at least 5-10 N/mm should be used. A device with lower stiffness will yield large margins of error on judgements of relative roughness. Also, due to the very low absolute curvature of $\Psi(I)$ with such a highly compliant haptic device, the sensitivity of subjects to changes in element spacing will be very poor. Since $\Psi(I)$'s curvature also tends to decrease with increasing probe size, if a high compliance device must be used for texture simulation, the probe size should be as small as possible if measures of roughness sensitivity are to have any meaning..

Whether or not an optimal stiffness level exists for roughness perception is still an open question. Clearly, a greater range of roughness, lower overall inter-subject variability and greater sensitivity

to changes in element spacing can be achieved with lower compliance. Figure 9.3 shows that curvature and maximum roughness increase in a mostly linear fashion with increasing stiffness. It seems likely that this trend could not continue indefinitely since neuroreceptors would eventually saturate. Determining the compliance at which this occurs will require the use of a device with greater stiffness than that of the MLHD.

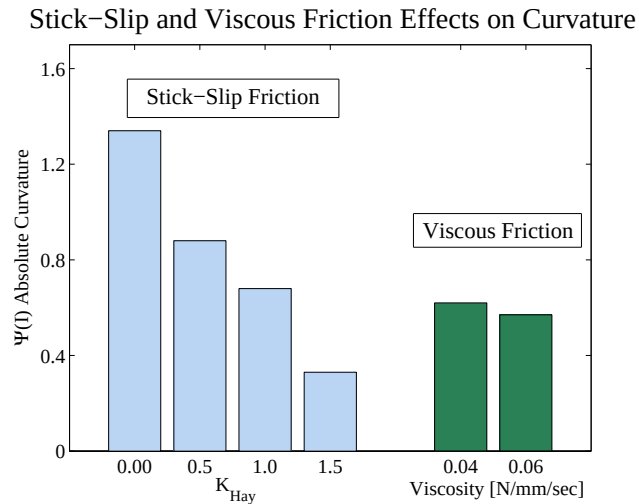


Figure 9.4: The effects of stick-slip friction (Hayward Model) and viscous friction on the curvature of the psychophysical function for roughness.

Frictional effects also profoundly affect the nature of the psychophysical function for roughness. The addition of horizontal stick-slip forces to the geometry-based texture produced by the CSA, flattens $\Psi(I)$, causing subjects to feel the surface as rougher, particularly at element spacings which previously felt smooth. Viscous friction does not have the same effect, although the experiments of Chapter 8 involve only small changes in viscous friction level and are perhaps not sufficient to base such a conclusion upon. Viscous friction appears to decrease $\Psi(I)$'s curvature dramatically but changing levels of viscous friction apparently have little additive effect (see Figure 9.4).

That stick slip friction does not affect the DP but reduces the curvature of $\Psi(I)$ (see Figure 9.4) provides a *caveat* for the use of haptic devices with high levels of mechanical friction in the study of virtual texture. If a device has significant intrinsic friction, subjects are likely to find it more difficult to discriminate between the levels of roughness which result from changes in element spacing. Thresholding experiments, such as JNDs, will therefore return higher values than those performed with real textures or with friction-less devices such as the MLHD.

The effects on roughness perception of changing probe size, shape and compliance are significant, accounting for previous authors' findings of differences between real and virtual textures. The need to model these effects or at least consider them when studying the psychophysics of texture is apparent. It is also demonstrably possible to achieve a texture with a haptic device, whose roughness is perceived by subjects to be virtually identical to that of real textures. Friction and compliance will affect the perception of texture roughness in significant ways suggesting that texture models need to incorporate them in order to achieve realism. Frictional and compliance effects also suggest that future device design, if it is meant to display realistic texture, should strive to achieve minimal mechanical friction and maximal achievable stiffness levels.

9.2 The Physical Property Characterizing Roughness

The physical property which is felt as roughness appears to be the variability in the force experienced by subjects and transmitted to their hand by the manipulandum. Other studies have demonstrated that, for the bare finger, tangential forces and the first derivative of force to some extent correlate with subjective roughness [80, 126]. Klatzky and Lederman have previously shown, in real texture studies, that probe and texture geometry relate directly to the perception of texture roughness [66, 79, 82]. This leads to the conclusion that probe vibratory motion is related to texture perception. Yoshioka [156] has demonstrated that vibratory power appears to correlate with roughness perception, while Lin [104, 105] has demonstrated that a virtual spherical probe-texture model has an acceleration function which resembles the quadratic $\Psi(I)$ s found by Klatzky for real probes on dithered conical textures.

In this thesis, position and force data were captured as subjects explored textures and made estimates of roughness. The psychophysical measures of roughness were used to generate a psychophysical function, $\Psi(I)$, which related roughness to the stimulus of element spacing. The position and force data were processed to yield a function similar to $\Psi(I)$, which related the measure of some physical property to element spacings. For example, the probe z -axis instantaneous velocity might be found for each element spacing in $\Psi(I)$, producing the analogous physical function, $\Phi(I)$

In this thesis the assumption was made that a correlation between $\Psi(I)$ and $\Phi(I)$ can be taken as evidence of causality. Correlation coefficients between the various $\Phi(I)$'s for different measures of physical properties were taken. For the point-probe and sinusoidal grating experiments of Chapter

3, it became immediately apparent that variability in force, as measured by the power in a power spectral density periodogram of the z -axis force signal, was very strongly correlated with roughness. Multilinear regression, taking all of the investigated parameters into account, confirmed this, with force variability accounting for 98.4% of the variation in the roughness function.

With each successive experiment (trapezoidal gratings, dithered conical texture with spheres, conical probes, compliance and friction experiments), the same physical properties were measured and correlations to the roughness function examined. Since these subsequent experiments used a much smaller set of element spacings than that of the sinusoidal texture experiment, correlations between $\Phi(I)$ and $\Psi(I)$ were not as reliable. Several other properties, which had correlated poorly with roughness in the sinusoid experiment, now showed good correlation. Notably, probe instantaneous velocity and acceleration often showed excellent levels of correlation. However, force variability continued to correlate well with roughness across all experiments (with the exception of friction) and thus must be the prime candidate for the physical property which characterizes roughness.

It is notable that the friction experiment showed that for both stick-slip and viscous friction, correlation between roughness and z -axis force variability declined as friction levels increased. Presumably, the introduction of horizontal force variations affects roughness perception and thus measuring only the z -axis force variability is inadequate to characterize roughness. All other measures of physical properties, taken, as they were, solely in the z axis, showed a similar decline in correlation with roughness as friction increased.

The finding that force variability is strongly correlated with roughness implies that it might not be necessary to actually simulate geometry in order to accurately reproduce the $\Psi(I)$ of a real surface. Rather, the force variability of a probe moving over a texture could be recorded and played back. This finding validates the long history, in haptic texture simulation, of generating only forces, either with a stochastic algorithm [34, 39, 124, 125] or by measuring the force spectrum of a probe and playing it back via a haptic device [34, 86]. It seems clear that such methods, if carefully calibrated could produce textures which accurately represent the roughness of the real surfaces they model.

9.2.1 Texture's Physical Properties and Neuroreceptors

The vibrational response frequencies of the neuroreceptors in human skin are relatively well known [59, 154]. If variability in force characterizes roughness, it should be possible to band-limit the

force-signal to the receptors' response frequencies and determine which band correlates best with roughness. Correlation with a particular neuroreceptor's band would be strong evidence that that receptor was involved in roughness perception.

In this thesis, the PSD was band-limited to two bandwidths: 5-50 Hz and 50-500 Hz corresponding to the receptive bands of the FA1 and FA2 neuroreceptors respectively. The variability of the force in each of these bandwidth-limited force signals was determined to create a $\Phi(I)$ and this was correlated with $\Psi(I)$. For sinusoidal gratings and point-probes, the correlation with roughness for the FA1 $\Phi(I)$ was considerably stronger than that of the FA2 $\Phi(I)$. The correlation was not, however, as high for the FA1's as it was for the full force signal. This leads to the conclusion that, while the FA1s appear to be most responsible for roughness perception, the FA2s may play a subsidiary role. Identical experiments for trapezoidal gratings, dithered conical textures with spheres and cones as probes, compliance levels and friction failed to delineate meaningfully between the two bandwidths. While it seems obvious that the FA1s are the primary receptor for roughness, the FA2s cannot be completely ruled out. It would be very interesting if both receptors were somehow needed for the perception of roughness, implying high level cognitive processing combines their signals meaningfully. Clearly, further study in this area is warranted to delineate the FA1 and FA2 roles in roughness perception.

9.3 JND for Roughness with Virtual Textures

One of the advantages of using a haptic device to display virtual texture is the ability to perform psychophysical tests, such as JND determinations, easily and quickly. Since the number of physical plates required in an adaptive JND experiment grows factorially with the number of steps in the experiment, it is not feasible to create enough of them. The haptic device allows a researcher to control texture parameters over a continuous range and adapt texture features to previous subject responses nearly instantaneously. This prevents subject fatigue and allows experiments to be much more sophisticated than would be possible with real textures. For example, with the setup in the current thesis it is possible to have a subject perform up to 12 separate JND determinations in the course of an hour.

The JND determinations in this thesis used Kaernbach's unforced weighted up-down adaptive staircase technique to examine the JND for roughness based on changes in element spacing. Three sets of experiments were carried out examining the roughness JND and its response to changes in

probe size (Chapter 5, Section 5.6), probe shape (Chapter 6, Section 6.6) and compliance (Chapter 7, Section 7.6). The JND for roughness with respect to element spacing had not previously been determined with either real or virtual textures, although the JND for roughness with respect to the amplitude of a sinusoidal grating has been investigated [67].

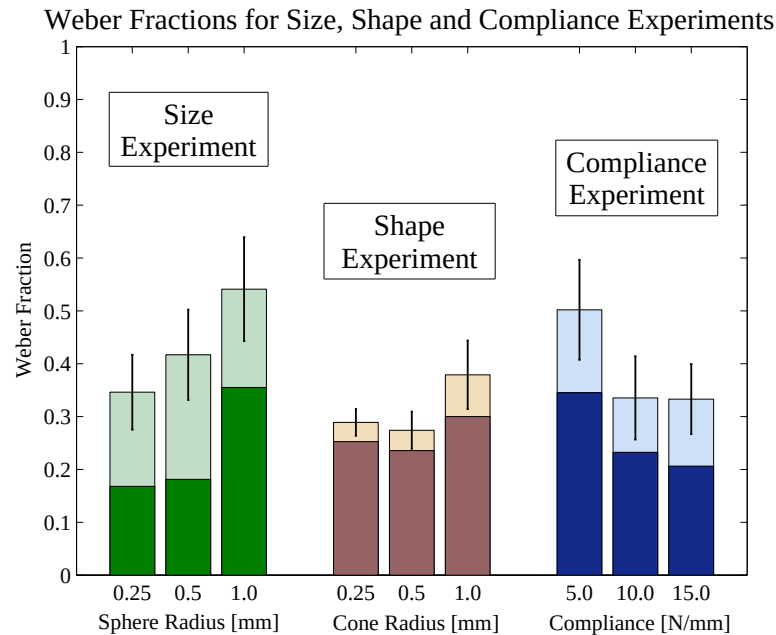


Figure 9.5: Weber fractions for probe size, probe shape and compliance experiments. Dark areas represent the minimum Weber fraction for that probe type while light areas represent the mean over all base textures. Error bars indicate $\pm$ the standard error.

The primary goals in examining the JND were to create a record of the roughness threshold for future researchers and to examine how the thresholds are affected by changes in probe size, shape and compliance. The relationship of the JND to the psychophysical function for roughness is also examined.

The Weber fraction, as described in Section 1.2.1, is a standardized way of describing a JND. It is determined by dividing the JND by the base texture spacing (BTS) at which it is found. The mean of the Weber fraction over all BTS for a single probe type is then calculated. The Weber fractions for the each probe type in the three JND experiments are shown in Figure 9.5. Ideally, the JND/BTS ratio for a single probe type should be constant for all BTSs. However, as demonstrated by the size of the standard errors, there is considerable variation in each probe type's JND. Sections 5.6, 6.6 and 7.6 show that JND depends on BTS in a complex way. The possibility of runaway JNDs (see Chapter 2, Section 2.3.3 for a description of the runaway phenomena) and the decreasing

Probe Type	Experiment Type					
	Probe Size		Probe Shape		Compliance	
	Mean	Min	Mean	Min	Mean	Min
Type 1	0.35±0.07	0.17	0.29±0.02	0.25	0.50±0.10	0.35
Type 2	0.42±0.09	0.18	0.27±0.04	0.24	0.34±0.08	0.23
Type 3	0.54±0.10	0.36	0.38±0.07	0.30	0.33±0.07	0.21
Mean	0.44	0.24	0.31	0.26	0.39	0.26

Table 9.1: Weber fractions for probe size, shape and compliance experiments. Each experiment has 3 probe types. For the size and shape experiments types 1-3 are probe radii of 0.25, 0.50 and 1.0 mm respectively. For the compliance experiment types 1-3 are probes with compliances of 5.0, 10.0, and 15.0 N/mm respectively. The mean Weber fraction over probe types is shown in the last row.

slope of the psychophysical function as element spacing increases beyond the drop point, makes the larger BTS JNDs unreliable. As a result, the mean Weber fraction, which incorporates all BTSs for a probe type, may not be the best measure of JND. The minimum Weber fraction for each probe type is probably a better measure of the actual threshold for the detection of roughness change. The minimum Weber fractions are shown as dark bars in Figure 9.5 while the mean fractions are shown as light bars.

From the figure, it can be seen that the mean Weber fractions are lowest for cone-shaped probes but, in general, it appears that they are remarkably uniform. The overall mean Weber fraction was found to be 0.38. This is fairly high when compared with similar determinations of roughness discriminability with the bare finger which range from 0.05-0.12 [49, 72, 98] for spacings larger than about 0.2 mm. However, for finer surfaces, a similar Weber fraction of 0.38 has been established by Hollins for the bare finger[49].

The difference between fine and coarse surface bare-finger Weber fractions has been attributed to a duplex theory for roughness perception which states that spatial effects produce roughness for coarse textures while vibrational effects produce roughness for fine textures [49]. While the textures in this thesis are almost all coarse (> 0.1 mm spacings), the introduction of a probe requires subjects to rely on vibratory cues for roughness sensation. Thus a JND of 0.38 is in keeping with Hollins findings for fine textures.

Since indirect texture perception is clearly mediated by vibratory effects and the Weber fraction is here determined to be the same as that for direct perception of fine surfaces, this set of experiments

adds evidence for the duplex theory that direct texture perception of fine surfaces is mediated by temporal cues.

The geometric interactions between probe and texture complicate the interpretation of the JND because the psychophysical function with non point-probes is not linear. Thus, depending on where on the quadratic function the BTS for a JND determination occurs, subjects' sensitivity to changes in spacing may vary. The minimum JND may thus be a more consistent measure of the "best" threshold achievable. The minimum Weber fraction for spherical probes on dithered conical textures is 0.17. This falls between the thresholds for coarse and fine textures with the bare finger mentioned above. The minimum fraction for conical probes is 0.24. The larger fraction for conical probes may be a result of higher noise levels in the path followed by the conical probe over texture or it may simply reflect uncertainty in the JND determination.

The mean and minimum Weber fractions for all levels of compliance are very similar to those of the spherical and conical probes. In particular, the highest two levels of compliance yield virtually identical mean and minimum values. This suggests that the Weber fractions determined are not dependent on device compliance, once a certain minimum stiffness has been achieved. The determined Weber fractions are therefore likely due to actual human discriminatory capabilities and not to hardware limitations.

9.4 Contributions

This thesis has explored the psychophysics of texture perception using a constraint surface algorithm and a state-of-the-art magnetic levitation haptic device. The CSA has allowed investigation of the effects of probe-texture geometric interaction on the perception of roughness. The probe has been modeled as an object with physical size, shape and compliance, interacting with texture elements that range from gratings to dithered truncated cones. Recording of subject roughness perception has permitted a detailed analysis of the human psychophysical functions for roughness and the determination of just-noticable difference thresholds for varying probe size, shape and compliance. An investigation of changes in roughness perception in the presence of stick-slip and viscous friction was also performed. Recordings of position and force data made during psychophysics experiments were used to study the physical determinants of subjective perceptions of roughness. These results are summarized in Table 9.2.

The primary contributions of this thesis therefore include the following:

Experiment Name	$\Psi(I)$				$\Phi(I)_{Fz}$ Var.	Minimum
	Shape	Curv.	DP	Max.	Correlation	JND
Sinusoidal Grating	Hockey Stick	–	–	–	Strong	–
Trapezoidal Grating	Sigmoidal	–	$\uparrow \bar{c}$ Prb. Sz.	–	Strong	–
Dith./Spherical Probe	Quadratic	$\downarrow \bar{c}$ Prb. Sz.	$\uparrow \bar{c}$ Prb.Sz.	$\leftrightarrow \bar{c}$ Prb. Sz.	Strong	0.105 mm
Dith./Conical Probe	Third Order	–	$\uparrow \bar{c}$ Prb. Sz.	$\downarrow \bar{c}$ Prb. Sz.	Strong	0.116 mm
Dith./Compliance	Quadratic	$\downarrow \bar{c}$ Comp.	$\leftrightarrow \bar{c}$ Comp.	$\downarrow \bar{c}$ Comp.	Strong	0.165 mm
Dith./Friction	Quadratic	$\downarrow \bar{c}$ Frict.	$\leftrightarrow \bar{c}$ Frict.	$\leftrightarrow \bar{c}$ Frict.	Weak	–

Table 9.2: Primary experimental results. The shape of the psychophysical function for each experiment is shown. The effect of experiment factor (increasing probe size, compliance or friction levels) on $\Psi(I)$'s absolute curvature, drop point, and maximum, calculated from a second order fit to experimental data, is shown where applicable. The strength of the correlation of the physical function for z -axis force variability ($\Phi(I)_{Fz}$) with the psychophysical function is presented for all experiments. The minimum JND determined for three experiments is also shown.

- The creation of an experimental platform for the exploration of human texture perception and its relationship to physical phenomena.
- A demonstration that virtual haptic textures are a useful tool for performing psychophysical studies of texture perception and that virtual findings correlate well with real-world psychophysical properties.
- A demonstration that the perception of virtual texture depends on modeling the geometry of both texture *and* the exploring probe's size and shape
- A demonstration of the effects of compliance and friction on texture perception with implications for future hardware design.
- The discovery that texture roughness can be characterized by the physical property of force variability.
- An spectral analysis of the force signal which provides evidence that FA1 neural receptors are the receptors primarily responsible for mediating roughness perception.
- The creation of a record in the literature of roughness JNDs for virtual texture element spacing and their relationship to probe size, shape and compliance.

These contributions provide significant new insight into the perception of roughness and raise interesting questions for further investigation. They also provide an experimental platform and framework which should expedite future studies of texture perception.

9.5 Future Work

The constraint surface algorithm provides a way to control many of the parameters associated with texture. The experimental testbed designed for this thesis provides experimenters with the capability of manipulating conical texture element geometry to change element height, side angle, and top and bottom radii. It is also possible to manipulate the size, shape and compliance of the probe. Multiple friction models are available for application to textured surfaces. With changes to the parametric equations governing the constraint surface, the fundamental shape of the probe can also be easily manipulated.

The wealth of parameters and the ease with which they may be controlled suggests a number of different avenues of research to pursue. For example, the JNDs for element height, side angle, and dithering distance would all be interesting findings. Element height is analogous to sine texture amplitude and comparisons between various grating geometries could determine the most discriminable gratings. Comparison could also be made with the literature on known JNDs for virtual texture amplitude [67]. The recent development of an improved MLHD with a larger workspace and improved stiffness, resolution and bandwidth characteristics should facilitate improved texture simulations. The fidelity of smaller texture elements should be significantly better and a broader range of experiment parameters, such as compliance, could be explored.

One of the contributions of this thesis was the incorporation of velocity into the quasistatic geometric model developed by Klatzky *et al.* [66] (See Section 4.4). By taking probe velocity into account, Equation 4.16 of Section 4.4 adjusts the expected point of maximum roughness upward, to larger element spacings. This revised *dynamic* model assumes that a probe will continue its forward motion as it falls between elements. In order to contact the texture base rather than the side of an upcoming element, interelement spacing must increase for any significant probe velocity. Increasing element height, increasing probe velocity or increasing element side angles should, therefore, all result in larger DPs. This dynamic model is supported by the finding that the DP tends to increase as probe velocity increases for real textures and probes [63, 66, 82]. The CSA experimental testbed provides a straightforward way to verify the dynamic model. Subjects could perform magnitude

estimates of roughness with varying element heights and side angles and a psychophysical function for roughness could be determined. Simultaneous velocity measurements could be used to make model-based DP predictions for comparison with experimentally determined DP values.

The speed with which subjects move the probe over a textured surface results in vibrations which are sensed as roughness. The frequency of these vibrations is thus directly related to probe speed. Previous studies have tended to show little effect of speed on roughness with direct touch [72, 81, 93] but small but significant effects with indirect touch [63, 66, 82].

In this thesis, subjects were permitted to explore textures actively. Thus, they decided the speed with which to move the probe. The subjects clearly have some knowledge of their hand speed via the kinesthetic sense. It is possible that they adjust this speed to acquire texture information at a particular frequency. For example, since the FA1 receptor seems to be primarily responsible for roughness perception, it is possible that the speed selected maximizes the power in the FA1 bandwidth (5-50 Hz) in order to estimate roughness as well as possible. This can only happen when subjects control the probe motion actively. It is possible to use the CSA to present subjects with a continuously moving conveyor-belt of texture which moves under the probe tip. The probe can be held stationary, or subjects can be allowed to move with or against the motion of the conveyor in a hybrid of active and passive exploratory states. This setup would test the hypothesis that subjects control motion speed, a form of exploratory procedure, to maximize roughness information. If subjects use their kinesthetic sense to inform their discrimination of roughness, then active speed control should be better than passive, with hybrid control intermediate between them.

The exploratory procedures of subjects could be further analyzed since access to position and force data is possible. It should be straightforward to examine the patterns in probe positioning, velocity and acceleration as subjects move the probe over a variety of surfaces. It is possible, for example, that the choice of motion direction may be related to the type of texture subjects encounter. Motion direction may be manipulated by subjects in order to maximize information about a texture's perceptual characteristics. For a grating this might mean motion directed perpendicular to grating elements whereas for an isotropic surface a circular or random motion might be preferred.

The amount of force applied by subjects might also vary depending on texture characteristics. There is some evidence that the applied force may affect texture perception [66, 76, 81, 108]. The force applied by subjects is countered by the haptic device and is thus measurable. A set of experiments designed to vary texture parameters such as element height, surface friction, *etc.* could be

developed and subjects' force applications could be measured along with psychophysical measures of texture perception. The effects of these parameters on the applied force could then be determined.

The forces generated by the haptic device are actually a combination of the force applied by the user and forces resulting from the interaction of probe and texture. In a static setting, the applied force and the device response should be identical, equal and opposite. However, since the virtual texture is perceived through probe vibrations, it is clear that probe dynamics must play a role in the sensation of a texture's roughness. Probe dynamics are filtered by the hand in a way which is, as yet, poorly understood. If a force sensor were introduced into the handle of the haptic device, it would be possible to measure the applied hand forces, while at the same time measuring the device response. By subtraction, it should be possible to characterize the effects of the hand on vibrations that are perceived as texture.

It should also be possible to further analyze the neuroreceptors in the hand which respond to texture vibrations. A determination of the JND or of the psychophysical function for roughness, $\Psi(I)$, could be made while selectively adapting one of the FA1 or FA2 channels. To investigate the FA1 channel, for example, it would be possible to pre-adapt a subject's hand to the FA1 bandwidth with vibrations at 5-50 Hz and then re-evaluate JND or $\Psi(I)$. A significant decline in sensitivity would indicate the importance of this channel for roughness perception.

The CSA and the MLHD could also be used as an effective platform to stimulate neuroreceptors with complex texture patterns while directly examining neural outputs. Currently, such stimulators tend to be mechanical textures mounted in a variety of ways and then explored by subjects (usually primates) while electrodes monitor neural discharges [12, 20, 23, 27, 28, 71, 97]. The platform described in this thesis could be used to present a wide range of textures to a subject, easily switching between parameter values and reducing experimenter workload.

The presence or absence of vibratory noise and its effects on texture perception could also be explored. Since even the phase of a sinusoid may change the perception of a texture [7], the addition of small amplitude noise may impair texture perception. This may be the effect seen when a predominantly vertical texture has stick-slip friction applied to it on the horizontal plane as observed in Section 8.4. Small vibrations at different frequencies could be played on top of a constraint surface generated by probe-texture geometry and the resulting changes in texture sensitivity and perception investigated. Such a study might have significance for the use of virtual textures in settings where low-level mechanical device vibrations might affect virtual texture presentation. Small vibrations

could also provide a way to systematically degrade the haptic sense of texture in experiments where comparisons are made of the relative effectiveness of touch and other senses [33].

Direct extensions of the work in this thesis could include developing a dynamic model of texture based on force variability, the property which seems to correlate best with roughness perception. Such a force variability model would not require the intermediate use of geometric calculations to generate output forces. This would reduce the texture simulation's computational overhead and potentially allow for the use of more complex virtual textures.

It should also be possible to extend the CSA model to incorporate other probe shapes and texture elements. The CSA described in this thesis relies on the symmetry of probe and element shapes to permit fast calculations for the probe path. The simplest extension of the CSA would explore other symmetric probe and element shapes such as cylinders and swept parabolas. The CSA could be further extended to arbitrary probe and element shapes by doing local collision detection with only nearby elements, based on the position of the haptic interaction point. Such a task, while computationally intensive, exploits the 2.5 dimensional nature of texture to constrain the number of possible elements involved. The full 6 degrees of freedom of the MLHD could then be used to apply x and y -axis forces as well as torques to the exploring probe. Such a 6 DOF simulation would allow investigation of the importance of probe attack angle on texture perception. It would also permit completely irregular probe and element shapes to be studied.

The ultimate importance of all of these investigations lies in determining the capabilities of the human perceptual system and providing a better understanding of system (both hardware and algorithmic) requirements for simulating realistic virtual texture. More realistic textures will ultimately be necessary for virtual training purposes, teleoperated tasks and in general haptic simulations. The constraint surface algorithm used together with a high-fidelity haptic device such as the MLHD, can be used as an important tool for improving the understanding of human texture perception.

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Appendices

Appendix A

Data Fitting Equations, Fit Parameters and Statistical Analysis Tables for Selected Experiments

Roughness magnitude estimates are plotted against texture period and the data is fitted using polynomial equations of second and/or third order on log-log and unlogged plots. Similar fits to MLHD physical parameter data plotted against texture period are also performed. The following tables show equations of these fits as well as their R^2 values. Tables showing fit parameters and statistical analysis are also included where such details are not found in the body of the thesis.

A.1 Sinusoidal Grating Texture

See caption headings for R^2 values.

A.2 Trapezoidal Grating Texture

A.2.1 Psychophysical Functions for Roughness

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -1.65x^2 + 1.65x + 0.87$	0.97	$0.82x^3 - 2.60x^2 + 1.92x + 0.86$	0.98
0.50	$y = -1.77x^2 + 2.05x + 0.72$	0.98	$-0.57x^3 - 1.12x^2 + 1.86x + 0.73$	0.98
1.0	$y = -0.85x^2 + 1.51x + 0.73$	0.93	$-4.37x^3 + 4.19x^2 + 0.06x + 0.79$	0.98
1.5	$y = 0.08x^2 + 0.91x + 0.68$	0.95	$-4.33x^3 + 5.07x^2 - 0.53x + 0.73$	1.0

Table A.1: Second and third order fits on a log-log plot, to roughness estimation profiles for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Factor	DOF	F	p-value
curvature	3/92	72.66	< 0.0001
Curve Height	3/92	118.38	< 0.0001
2nd Order Maxima	3/92	0.77	> 0.05
3rd Order Maxima	3/92	0.89	> 0.05

Table A.2: Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to subject roughness estimates for trapezoidal gratings.

Probe Radius [mm]	Logistic Fit	SSE
0.25	$y = 0.78 + \frac{0.46}{1+e^{-16.21(x-0.10)}}$	0.0131
0.50	$y = 0.69 + \frac{0.60}{1+e^{-15.18(x-0.17)}}$	0.0035
1.0	$y = 0.80 + \frac{0.56}{1+e^{-16.49(x-0.31)}}$	0.0044
1.5	$y = 0.70 + \frac{0.68}{1+e^{-9.45(x-0.39)}}$	0.0024

Table A.3: Logistic fits to roughness magnitude estimation on a log-log plot for trapezoidal gratings. Four probe sizes are used. Sum of square errors are shown for individual fits beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -1.27x^2 + 9.65x + 0.67$	0.81	$y = 0.52x^3 - 6.65x^2 + 25.86x - 12.49$	0.97
0.50	$y = -1.52x^2 + 12.67x + 5.00$	0.93	$y = 0.42x^3 + 5.85x^2 + 25.70x + 15.57$	0.98
1.00	$y = -1.37x^2 + 12.99x + 7.04$	0.96	$y = -0.14x^3 + 0.13x^2 + 8.50x + 3.39$	0.97
1.50	$y = -0.53x^2 + 7.74x + 3.51$	0.97	$y = -0.34x^3 + 3.02x^2 + 2.96x + 5.18$	0.99

Table A.4: Second and third order fits on a unlogged plot, to roughness estimation profiles for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

A.2.2 Physical Parameter Functions

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -0.03x^2 + 0.22x - 0.08$	0.92	$y = 0.01x^3 - 0.10x^2 + 0.45x - 0.27$	0.98
0.50	$y = -0.03x^2 + 0.29x + 0.19$	0.98	$y = 0.00x^3 + 0.05x^2 + 0.36x + 0.24$	0.98
1.00	$y = -0.01x^2 + 0.23x + 0.18$	0.95	$y = -0.02x^3 + 0.15x^2 + 0.25x + 0.21$	0.99
1.50	$y = 0.03x^2 + 0.00x + 0.07$	0.99	$y = -0.01x^3 + 0.12x^2 + 0.28x + 0.30$	1.00

Table A.5: Second and third order fits to z -axis position standard deviation functions for trapezoidal gratings. The functions are based on the cross-subjects averaged standard deviation. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -1.82x^2 + 13.82x - 5.78$	0.85	$y = 0.63x^3 - 8.37x^2 + 33.54x - 21.79$	0.97
0.50	$y = -2.09x^2 + 17.70x + 12.90$	0.95	$y = 0.35x^3 + 5.72x^2 + 28.64x + 21.78$	0.97
1.00	$y = -1.51x^2 + 16.66x + 15.90$	0.96	$y = -0.63x^3 + 5.00x^2 + 2.94x + 0.02$	0.99
1.50	$y = -0.08x^2 + 7.85x + 7.52$	0.97	$y = -0.62x^3 + 6.32x^2 + 11.41x + 8.11$	0.99

Table A.6: Second and third order fits to mean instantaneous velocity data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -25.41x^2 + 191.1x - 146.7$	0.86	$7.04x^3 - 98.42x^2 + 410.8x - 325.1$	0.94
0.50	$y = -30.38x^2 + 259.8x - 252.1$	0.93	$0.052x^3 - 30.91x^2 + 261.4x - 253.4$	0.93
1.0	$y = -14.87x^2 + 225.7x - 276.8$	0.90	$-20.35x^3 + 196.2x^2 - 409.5x + 239.0$	0.98
1.5	$y = 26.22x^2 - 26.65x - 15.642$	0.98	$-8.48x^3 + 114.2x^2 - 291.3x + 199.3$	0.99

Table A.7: Second and third order fits to mean kinetic energy data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -170.2x^2 + 1205x + 369.4$	0.67	$86.32x^3 - 1065x^2 + 3898.9x - 1818$	0.94
0.50	$y = -210.2x^2 + 1675x - 542.7$	0.91	$55.35x^3 - 784.1x^2 + 3402x - 1945$	0.96
1.0	$y = -171.6x^2 + 1662x - 950.9$	0.95	$-44.10x^3 + 285.6x^2 + 285.5x + 166.6$	0.97
1.5	$y = -51.82x^2 - 906.5x - 249.1$	0.94	$-71.53x^3 + 689.8x^2 - 1326x + 1564$	0.99

Table A.8: Second and third order fits to mean instantaneous acceleration data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -1.14x^2 + 8.33x - 1.95$	0.80	$0.42x^3 - 5.45x^2 + 21.32x - 12.49$	0.96
0.50	$y = -1.26x^2 + 10.53x - 5.92$	0.93	$0.14x^3 - 2.68x^2 + 14.81x - 9.39$	0.94
1.0	$y = -0.87x^2 + 10.31x - 8.22$	0.90	$-0.74x^3 + 6.78x^2 - 12.71x + 10.48$	0.98
1.5	$y = -0.57x^2 - 1.74x - 0.55$	0.95	$-0.58x^3 + 6.59x^2 - 16.37x + 15.25$	0.99

Table A.9: Second and third order fits to mean z -axis force signal total power data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -1.07x^2 + 7.97x - 4.84$	0.84	$0.35x^3 - 4.65x^2 + 18.75x - 13.59$	0.95
0.50	$y = -1.15x^2 + 9.66x - 7.98$	0.93	$0.12x^3 - 2.42x^2 + 13.48x - 11.08$	0.94
1.0	$y = -0.87x^2 + 9.89x - 10.49$	0.90	$-0.67x^3 + 6.04x^2 - 10.91x + 6.40$	0.98
1.5	$y = 0.43x^2 + 2.22x - 2.88$	0.94	$-0.58x^3 + 6.44x^2 - 15.87x + 11.81$	0.99

Table A.10: Second and third order fits to mean z -axis force signal FA1 band (5-50 Hz) power data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -0.06x^2 + 0.38x - 0.24$	0.36	$0.04x^3 - 0.50x^2 + 1.71x - 0.84$	0.68
0.50	$y = -0.10x^2 + 0.82x - 0.53$	0.91	$0.02x^3 - 0.33x^2 + 1.52x - 1.10$	0.94
1.0	$y = -0.05x^2 + 0.76x - 0.77$	0.93	$-0.06x^3 + 0.52x^2 - 0.95x + 0.61$	0.99
1.5	$y = 0.09x^2 - 0.10x + 0.10$	0.98	$-0.04x^3 + 0.45x^2 - 1.18x + 0.97$	0.99

Table A.11: Second and third order fits to mean z -axis force signal FA2 band (> 50 Hz) power data for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -0.19x^2 + 1.48x - 0.91$	0.90	$0.03x^3 - 0.47x^2 + 2.30x - 1.57$	0.92
0.50	$y = -0.17x^2 + 1.60x - 1.20$	0.95	$-0.01x^3 - 0.10x^2 + 1.37x - 1.02$	0.96
1.0	$y = -0.10x^2 + 1.56x - 1.54$	0.88	$-0.17x^3 + 1.62x^2 - 3.62x + 2.67$	0.98
1.5	$y = -0.25x^2 - 0.47x - 0.61$	0.97	$-0.06x^3 + 0.87x^2 - 2.32x + 2.11$	0.98

Table A.12: Second and third order fits to mean maximum power in the z -axis force signal for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-0.19	1.31	3.86	3.55
0.50	-0.17	1.56	4.63	4.64
1.0	-0.10	2.06	7.83	5.08
1.5	0.25	2.56	0.93	8.16

Table A.13: The trapezoidal texture period at which the maximum power in the force signal occurs based on 2nd and 3rd order curves fitted to data averaged across subjects. Curvature of the 2nd order fitted curve on an unlogged plot of the maximum power in the force signal versus spacing is shown. For comparison, the roughness maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	10.49	< 0.0001
2nd Order Maxima	3/92	0.78	> 0.05
3rd Order Maxima	3/92	1.73	> 0.05

Table A.14: Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the maximum power which occurs in the force signal.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -0.96x^2 + 7.11x + 3.66$	0.55	$0.66x^3 - 7.82x^2 + 27.77x - 13.11$	0.90
0.50	$y = -1.14x^2 + 8.88x - 0.76$	0.78	$0.54x^3 - 6.77x^2 + 25.84x - 14.52$	0.96
1.0	$y = -1.38x^2 + 10.69x - 4.43$	0.81	$0.42x^3 - 5.76x^2 + 23.89x - 15.15$	0.89
1.5	$y = -1.05x^2 - 9.00x - 4.27$	0.93	$-0.19x^3 + 0.88x^2 + 3.17x + 0.45$	0.95

Table A.15: Second and third order fits to frequency at which maximum power in z -axis force signal data occurs for trapezoidal gratings. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Probe Radius [mm]	2nd Order Curv.	Predicted Max. [mm]	2nd Order Max. [mm]	3rd Order Max [mm]
0.25	-0.96	1.31	3.72	2.71
0.50	-1.14	1.56	3.89	2.96
1.0	-1.38	2.06	3.88	3.20
1.5	-1.05	2.56	4.28	4.43

Table A.16: The trapezoidal texture period at which the frequency of the maximum power in the force signal occurs based on 2nd and 3rd order curves fitted to data averaged across subjects. Curvature of the 2nd order fitted curve on an unlogged plot of the frequency of the maximum power in the force signal versus spacing is shown. For comparison, the roughness maxima predicted by the geometric model are also shown. Results are shown for four probe sizes.

Factor	DOF	F	p-value
Curvature	3/92	3.63	< 0.02
2nd Order Maxima	3/92	3.55	< 0.02
3rd Order Maxima	3/92	25.02	< 0.0001

Table A.17: Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the frequency at which maximum power occurs in the force signal for trapezoidal gratings.

	0.25 mm Probe		0.5 mm Probe		1.0 mm Probe		1.5 mm Probe	
Parameter	Corr. C.	p	Corr. C.	p	Corr. C.	p	Corr. C.	p
Mean Position	0.78	< 0.005	0.57	> 0.05	-0.91	< 0.0005	-0.98	< 0.0001
Velocity	0.98	< 0.0001	0.99	< 0.0001	0.97	< 0.0001	0.98	< 0.0001
Acceleration	0.93	< 0.0001	0.99	< 0.0001	0.98	< 0.0001	0.99	< 0.0001
Energy	0.97	< 0.0001	0.95	< 0.0001	0.91	< 0.0001	0.95	< 0.0001
Position Std	0.94	< 0.0001	0.95	< 0.0001	0.92	< 0.0001	0.92	< 0.0001
Mean Force	0.53	> 0.05	0.55	> 0.05	0.91	< 0.0001	0.96	< 0.0001
Max Power	0.93	< 0.0001	0.93	< 0.0001	0.90	< 0.0005	0.93	< 0.0001
Freq. Max Pow.	0.90	< 0.0005	0.95	< 0.0001	0.83	< 0.005	0.89	< 0.0005
FA1 Power	0.97	< 0.0001	0.97	< 0.0001	0.94	< 0.0001	0.96	< 0.0001
FA2 Power	0.64	< 0.05	0.98	< 0.0001	0.92	< 0.0001	0.93	< 0.0001
Total Power	0.97	< 0.0001	0.98	< 0.0001	0.94	< 0.0001	0.95	< 0.0001

Table A.18: Correlation coefficients for various physics parameter functions when compared to the roughness psychophysical functions of trapezoidal gratings.

A.3 Dithered Cone Texture with Spherical Probes

A.3.1 Psychophysical Functions for Roughness

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -1.59x^2 + 0.73x + 1.06$	0.88	$y = 1.88x^3 - 2.88x^2 + 0.66x + 1.13$	0.98
0.50	$y = -1.50x^2 + 0.86x + 1.00$	0.91	$y = 0.25x^3 + 1.67x^2 + 0.85x + 1.01$	0.91
1.00	$y = -1.23x^2 + 0.88x + 0.93$	0.87	$y = -1.38x^3 + 0.29x^2 + 0.94x + 0.88$	0.92
1.50	$y = -0.92x^2 + 0.81x + 0.87$	0.81	$y = -2.36x^3 + 0.69x^2 + 0.90x + 0.78$	0.95

Table A.19: Second and third order fits to mean normalized roughness estimates for dithered cone textures in a log-log plot. Four probe sizes are shown. R^2 values for individual fits are shown beside their equations.

A.3.2 Physical Parameter Functions

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -0.61x^2 + 2.83x + 4.82$	0.40	$y = 0.56x^3 - 5.66x^2 + 15.37x - 2.54$	0.78
0.50	$y = -0.96x^2 + 5.36x + 1.84$	0.54	$y = 0.60x^3 + 6.32x^2 + 18.65x + 5.96$	0.89
1.00	$y = -1.10x^2 + 6.72x + 0.30$	0.73	$y = 0.43x^3 + 4.94x^2 + 16.26x + 5.89$	0.90
1.50	$y = -1.11x^2 + 7.23x + 1.32$	0.87	$y = 0.22x^3 + 3.06x^2 + 12.07x + 4.16$	0.91

Table A.20: Second and third order fits to mean z -axis velocity for dithered cone gratings in an unlogged plot. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Factor	DOF	F	p-value
Curvature	3/92	26.28	< 0.0001
Curve Height	3/92	9.51	< 0.0001
2nd Order Maxima	3/92	193.20	< 0.0001
3rd Order Maxima	3/92	152.29	< 0.0001

Table A.21: Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the z -axis velocity.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.25	$y = -0.22x^2 + 0.93x + 3.85$	0.31	$y = 0.26x^3 - 2.59x^2 + 6.82x + 0.40$	0.70
0.50	$y = -0.33x^2 + 1.69x + 3.09$	0.38	$y = 0.28x^3 + 2.81x^2 + 7.84x + 0.52$	0.77
1.00	$y = -0.39x^2 + 2.23x + 2.34$	0.60	$y = 0.20x^3 + 2.16x^2 + 6.64x + 0.25$	0.87
1.50	$y = -0.44x^2 + 2.62x + 1.87$	0.78	$y = 0.08x^3 + 1.15x^2 + 4.37x + 0.84$	0.82

Table A.22: Second and third order fits to total power in the z -axis force signal for dithered cone textures in an unlogged plot. Four probe sizes are used. R^2 values for individual fits are shown beside their equations.

Factor	DOF	F	p-value
Curvature	3/92	5.36	< 0.005
Curve Height	3/92	0.24	> 0.05
2nd Order Maxima	3/92	1.15	> 0.05
3rd Order Maxima	3/92	22.83	< 0.0001

Table A.23: Significance of probe size effects, determined using a 1-way ANOVA, on curvature and maxima of a 2nd and 3rd order fit to the total power in the z -axis force signal..

A.4 Dithered Cone Texture with Conical Probes

A.4.1 Psychophysical Functions for Roughness

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.06	$y = -1.05x^2 + 0.15x + 1.32$	0.94	$y = 0.60x^3 - 1.19x^2 - 0.04x + 1.35$	0.98
0.25	$y = -0.99x^2 + 0.20x + 1.30$	0.90	$y = 0.44x^3 + 1.09x^2 + 0.06x + 1.31$	0.93
0.50	$y = -0.81x^2 + 0.32x + 1.22$	0.87	$y = -0.59x^3 + 0.67x^2 + 0.51x + 1.20$	0.92
1.00	$y = -0.29x^2 + 0.32x + 1.05$	0.73	$y = -1.12x^3 + 0.04x^2 + 0.68x + 1.01$	0.96
1.50	$y = -0.06x^2 + 0.26x + 0.94$	0.78	$y = -0.81x^3 + 0.13x^2 + 0.51x + 0.92$	0.95

Table A.24: Equations of 2nd and 3rd order fits to roughness versus element spacing in a log-log plot for five conical probe radii. The R^2 value for each fit is found beside it.

A.4.2 Physical Parameter Functions

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.06	$y = -1.29x^2 + 0.20x + 0.88$	0.91	$y = 0.46x^3 - 1.39x^2 + 0.06x + 0.90$	0.93
0.25	$y = -1.25x^2 + 0.24x + 0.87$	0.90	$y = -0.02x^3 + 1.24x^2 + 0.24x + 0.87$	0.90
0.50	$y = -0.93x^2 + 0.39x + 0.79$	0.74	$y = -1.46x^3 + 0.59x^2 + 0.86x + 0.73$	0.92
1.00	$y = -0.41x^2 + 0.46x + 0.62$	0.73	$y = -1.71x^3 + 0.01x^2 + 1.01x + 0.56$	0.99
1.50	$y = -0.00x^2 + 0.41x + 0.48$	0.86	$y = -1.09x^3 + 0.25x^2 + 0.76x + 0.44$	0.98

Table A.25: Coefficients of 2nd and 3rd order fits to z -axis velocity versus element spacing in a log-log plot for five conical probe radii. The R^2 value for each fit is found beside it.

A.5 Dithered Cone Texture and Compliance

A.5.1 Psychophysical Functions for Roughness

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.06	$y = -1.30x^2 + 0.19x + 0.38$	0.85	$y = 0.37x^3 - 1.39x^2 + 0.08x + 0.39$	0.86
0.25	$y = -1.22x^2 + 0.17x + 0.35$	0.83	$y = -0.05x^3 + 1.21x^2 + 0.18x + 0.35$	0.83
0.50	$y = -0.84x^2 + 0.34x + 0.22$	0.60	$y = -1.78x^3 + 0.43x^2 + 0.91x + 0.16$	0.88
1.00	$y = -0.18x^2 + 0.31x + 0.02$	0.53	$y = -1.79x^3 + 0.23x^2 + 0.87x + 0.04$	0.97
1.50	$y = 0.15x^2 + 0.20x + 0.11$	0.65	$y = -0.90x^3 + 0.36x^2 + 0.48x + 0.15$	0.84

Table A.26: Coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal versus texture spacing for five conical probe radii in a log-log plot. The R^2 value for each fit is found beside it.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
3.00	$y = -0.31x^2 + 0.18x + 0.63$	0.46	$y = -0.06x^3 - 0.27x^2 + 0.18x + 0.63$	0.47
5.00	$y = -0.83x^2 + 0.41x + 0.74$	0.95	$y = 0.13x^3 + 0.91x^2 + 0.41x + 0.75$	0.95
10.00	$y = -1.08x^2 + 0.56x + 0.93$	0.93	$y = 0.30x^3 + 1.28x^2 + 0.55x + 0.94$	0.94
15.00	$y = -1.24x^2 + 0.68x + 1.01$	0.96	$y = 0.73x^3 + 1.73x^2 + 0.66x + 1.04$	0.98

Table A.27: Coefficients of 2nd and 3rd order fits to the roughness in a standard plot for the compliance experiment. The R^2 value for each fit is found beside it.

A.5.2 Physical Parameter Functions

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
3.00	$y = -0.74x^2 + 0.37x + 0.55$	0.76	$y = -0.25x^3 - 0.57x^2 + 0.38x + 0.54$	0.77
5.00	$y = -1.32x^2 + 0.69x + 0.61$	0.88	$y = -0.25x^3 + 1.16x^2 + 0.70x + 0.60$	0.88
10.00	$y = -1.98x^2 + 1.08x + 0.78$	0.93	$y = 0.04x^3 + 2.01x^2 + 1.08x + 0.78$	0.93
15.00	$y = -2.08x^2 + 1.15x + 0.91$	0.92	$y = 0.40x^3 + 2.36x^2 + 1.13x + 0.93$	0.93

Table A.28: Coefficients of 2nd and 3rd order fits to the mean z -axis velocity versus element spacing in a log-log plot for four levels of compliance. The R^2 value for each fit is found beside it.

Probe Radius [mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
3.00	$y = -0.24x^2 + 0.10x - 0.13$	0.41	$y = 0.37x^3 - 0.50x^2 + 0.09x - 0.12$	0.49
5.00	$y = -0.77x^2 + 0.28x + 0.04$	0.85	$y = 0.80x^3 + 1.32x^2 + 0.25x + 0.07$	0.92
10.00	$y = -1.89x^2 + 1.00x + 0.30$	0.86	$y = -0.30x^3 + 1.68x^2 + 1.01x + 0.29$	0.86
15.00	$y = -2.26x^2 + 1.26x + 0.57$	0.84	$y = -0.24x^3 + 2.10x^2 + 1.27x + 0.56$	0.84

Table A.29: Coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal versus element spacing in a log-log plot for four levels of compliance. The R^2 value for each fit is found beside it.

A.6 Dithered Cone Texture with Friction

A.6.1 Psychophysical Functions for Roughness

k_{Hay} [N/mm]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.00	$y = -1.34x^2 + 0.68x + 0.95$	0.91	$y = 0.17x^3 - 1.46x^2 + 0.67x + 0.95$	0.91
0.50	$y = -0.88x^2 + 0.45x + 0.93$	0.88	$y = 0.29x^3 + 1.08x^2 + 0.43x + 0.94$	0.88
1.00	$y = -0.68x^2 + 0.37x + 0.95$	0.83	$y = 0.87x^3 + 1.28x^2 + 0.34x + 0.98$	0.93
1.50	$y = -0.33x^2 + 0.15x + 0.97$	0.60	$y = 0.47x^3 + 0.65x^2 + 0.13x + 0.98$	0.70

Table A.30: Coefficients of 2nd and 3rd order fits to the roughness magnitude estimation data in a log-log plot for four levels of stick-slip friction (k_{Hay}). The R^2 value for each fit is found beside it.

K_b [N/mm/sec]	2nd Order Fit	R^2	3rd Order Fit	R^2
0.04	$y = -0.62x^2 + 0.34x + 1.03$	0.77	$y = 0.44x^3 - 0.93x^2 + 0.32x + 1.05$	0.80
0.06	$y = -0.57x^2 + 0.29x + 1.05$	0.80	$y = 0.37x^3 + 0.83x^2 + 0.28x + 1.07$	0.83

Table A.31: Coefficients of equations for 2nd and 3rd order fits to the roughness magnitude estimation data in a log-log plot for two levels of viscous friction. The R^2 value for each fit is found beside it.

A.6.2 Physical Parameter Functions

K_{Hay}	2nd Order Fit	R^2	3rd Order Fit	R^2
0.00	$y = -1.66x^2 + 0.93x + 0.35$	0.90	$y = -0.39x^3 - 1.39x^2 + 0.95x + 0.33$	0.90
0.50	$y = -1.89x^2 + 0.99x + 0.31$	0.90	$y = -0.08x^3 + 1.83x^2 + 1.00x + 0.30$	0.90
1.00	$y = -1.58x^2 + 0.93x + 0.24$	0.87	$y = -0.17x^3 + 1.46x^2 + 0.94x + 0.24$	0.87
1.50	$y = -1.56x^2 + 0.78x + 0.24$	0.89	$y = -0.78x^3 + 1.03x^2 + 0.81x + 0.21$	0.91

Table A.32: Coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal in a log-log plot. The R^2 value for each fit is found beside it.

K_{Hay}	2nd Order Fit	R^2	3rd Order Fit	R^2
0.00	$y = -1.84x^2 + 1.05x + 0.81$	0.94	$y = -0.14x^3 - 1.75x^2 + 1.06x + 0.80$	0.94
0.50	$y = -1.88x^2 + 1.02x + 0.79$	0.92	$y = 0.08x^3 + 1.94x^2 + 1.01x + 0.79$	0.92
1.00	$y = -1.85x^2 + 1.00x + 0.77$	0.93	$y = -0.03x^3 + 1.83x^2 + 1.00x + 0.77$	0.93
1.50	$y = -1.86x^2 + 0.97x + 0.75$	0.95	$y = 0.11x^3 + 1.93x^2 + 0.97x + 0.75$	0.95

Table A.33: Coefficients of 2nd and 3rd order fits to the z -axis velocity data in a log-log plot for four levels of Hayward friction K_{Hay} . The R^2 value for each fit is found beside it.

Probe K_f	2nd Order Fit	R^2	3rd Order Fit	R^2
0.04	$y = -1.78x^2 + 0.99x + 0.26$	0.88	$y = -0.12x^3 - 1.69x^2 + 0.99x + 0.25$	0.88
0.06	$y = -1.81x^2 + 0.91x + 0.21$	0.87	$y = -0.38x^3 - 1.55x^2 + 0.92x + 0.19$	0.87

Table A.34: Viscous friction coefficients of 2nd and 3rd order fits to the total power in the z -axis force signal data in a log-log plot. The R^2 value for each fit is found beside it.

Probe K_f	2nd Order Fit	R^2	3rd Order Fit	R^2
0.04	$y = -2.05x^2 + 1.13x + 0.78$	0.93	$y = 0.36x^3 - 2.29x^2 + 1.11x + 0.79$	0.93
0.06	$y = -1.81x^2 + 0.97x + 0.76$	0.93	$y = -0.03x^3 - 1.79x^2 + 0.97x + 0.76$	0.93

Table A.35: Coefficients of 2nd and 3rd order fits to the mean z -axis velocity in a log-log plot for two levels of viscous friction. The R^2 value for each fit is found beside it.

Appendix B

Experimental Details

B.1 Roughness Magnitude Estimation Experiments

B.1.1 Sinusoidal Textures with Point-Probes

The sinusoidal texture experiment had a block of 7 demonstration trials and a block of 4 iterations each of the 33 experiment trials. Sine wave amplitude was 0.4 mm peak-to-peak. Translational and rotational proportional gains were 10.0 N/mm and 25.0 Nm/radian respectively while derivative gains were 0.04 N/mm/s and 0.5 N/radian/s for translation and rotation respectively. Experiment and demonstration trials were presented in random order within their respective blocks.

- Magnitude Estimation Experiment Subjects
 - 10 Male, 17 Female
 - 26 Right-handed, 1 Left-Handed
- 7 Demonstration Element Periods [mm]
 - [0.025, 0.25, 0.50, 1.00, 2.00, 4.00, 6.00]
- 33 Experiment Element Periods [mm]
 - [0.025, 0.050, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.75, 1.0, 1.25, 1.50, 1.75, 2.00, 2.25, 2.50, 2.75, 3.00, 3.25, 3.50, 3.75, 4.00, 4.25, 4.50, 4.75, 5.00, 5.25, 5.50, 5.75, 6.0]

B.1.2 Trapezoidal Textures with Spherical Probes

The trapezoidal texture experiment had four probe sizes, with 11 experiment periods and 3 iterations of each period for a total of 132 trials. Trials were blocked by probe size and the block order was randomized across subjects. Trials were randomized within blocks. There were 6 demonstration textures presented prior to each block, which used the same probe size as the following block. Demonstration textures were presented randomly within their blocks. Translational and rotational proportional gains were 10.0 N/mm and 25.0 Nm/radian respectively while derivative gains were 0.04 N/mm/s and 0.5 N/radian/s for translation and rotation respectively.

- Experiment Subjects
 - 17 Male, 9 Female
 - 23 Right-handed, 3 Left-Handed
- Trapezoidal Element Dimensions
 - $el_h = 0.42$ mm
 - $el_{pw} = 0.46$ mm
 - $el_{bw} = 1.04$ mm
 - $\alpha = 53^\circ$
- Spherical Probe Radii [mm]
 - [0.25, 0.50, 1.00, 1.50]
- 6 Demonstration Element Periods [mm]
 - [0.96, 1.96, 2.96, 3.96, 4.96, 5.96]
- 11 Experiment Element Periods [mm]
 - [0.96, 1.21, 1.46, 1.96, 2.46, 2.96, 3.46, 3.96, 4.46, 4.96, 5.96]

B.1.3 Dithered Conical Textures with Spherical Probes

The dithered conical texture experiment with spherical probes had four probe sizes, with 11 experiment periods and 3 iterations of each period for a total of 132 trials. Trials were presented randomly

to subjects. There were 6 demonstration textures for each of the four probe sizes. Therefore 24 randomly ordered demonstration trials were presented to the subjects prior to the actual experiment as a block. Translational and rotational proportional gains were 10.0 N/mm and 25.0 Nm/radian respectively while derivative gains were 0.04 N/mm/s and 0.5 N/radian/s for translation and rotation respectively. Dithering distance for conical elements was 40% of element spacing.

- Experiment Subjects
 - 17 Male, 7 Female
 - 20 Right-handed, 4 Left-Handed
- Conical Element Dimensions
 - $el_h = 0.42$ mm
 - $R_{top} = 0.23$ mm
 - $R_{base} = 0.52$ mm
 - $\alpha = 53^\circ$
- Spherical Probe Radii [mm]
 - [0.25, 0.50, 1.00, 1.50]
- 6 Demonstration Element Periods [mm]
 - [0.50, 1.50, 2.50, 3.50, 4.50, 5.50]
- 11 Experiment Element Periods [mm]
 - [0.50, 0.75, 1.00, 1.50, 2.00, 2.50, 3.00, 3.50, 4.00, 4.50, 5.50]

B.1.4 Dithered Conical Textures with Conical Probes

The dithered conical texture experiment with conical probes had five probe sizes, with 11 experiment periods and 3 iterations of each period for a total of 165 trials. Trials were presented randomly to subjects. There were 5 demonstration textures for each of the five probe sizes. Therefore 25 demonstration trials were presented to the subjects prior to the actual experiment as a randomly ordered block. Translational and rotational proportional gains were 10.0 N/mm and 25.0 Nm/radian respectively while derivative gains were 0.04 N/mm/s and 0.5 N/radian/s for translation and rotation respectively. Dithering distance for conical elements was 40% of element spacing.

- Experiment Subjects
 - 13 Male, 12 Female
 - 24 Right-handed, 1 Left-Handed
- Conical Element Dimensions
 - $el_h = 0.42$ mm
 - $R_{top} = 0.23$ mm
 - $R_{base} = 0.52$ mm
 - $\alpha = 53^\circ$
- Conical Probe Dimensions
 - Probe Height
 - * 0.25 mm
 - Conical Probe Radii [mm]
 - * [0.0625, 0.25, 0.50, 1.00, 1.50]
- 5 Demonstration Element Periods [mm]
 - [0.25, 0.75, 1.50, 3.00, 5.50]
- 11 Experiment Element Periods [mm]
 - [0.25, 0.50, 0.75, 1.00, 1.50, 2.00, 2.50, 3.00, 4.00, 4.75, 5.50]

B.1.5 Dithered Conical Textures and Compliance

The dithered conical texture and compliance experiment had one spherical probe size (0.50 mm radius) and four levels of compliance, with 11 experiment periods and 3 iterations of each period for a total of 132 trials. Trials were presented randomly to subjects. There were 6 demonstration textures for each of the four compliance levels. Therefore 24 demonstration trials were presented to the subjects prior to the actual experiment as a randomly ordered block. Translational proportional gains were set to one of the four experimental compliance levels. Rotational proportional gains were 25.0 Nm/radian respectively while derivative gains were 0.04 N/mm/s and 0.5 N/radian/s for translation and rotation respectively. Dithering distance for conical elements was 40% of element spacing.

- Experiment Subjects
 - 15 Male, 6 Female
 - 16 Right-handed, 5 Left-Handed
- Conical Element Dimensions
 - $el_h = 0.42$ mm
 - $R_{top} = 0.23$ mm
 - $R_{base} = 0.52$ mm
 - $\alpha = 53^\circ$
- Compliance Levels [N/mm]
 - [3.0, 5.0, 10.0, 15.0]
- 6 Demonstration Element Periods [mm]
 - [0.50, 1.50, 2.50, 3.50, 4.50, 5.50]
- 11 Experiment Element Periods [mm]
 - [0.50, 0.75, 1.00, 1.50, 2.00, 2.50, 3.00, 3.50, 4.00, 4.50, 5.50]

B.1.6 Dithered Conical Textures and Friction

The dithered conical texture and friction experiment had one probe size (0.50 mm radius) and four levels of stick-slip friction and two levels of viscous friction, with 10 experiment periods and 3 iterations of each period for a total of 180 trials. Trials were presented randomly to subjects. There were 5 demonstration textures for each of the 6 friction levels. Therefore 30 demonstration trials were presented to the subjects as a randomly ordered block prior to the actual experiment. Translational and rotational proportional gains were 10.0 N/mm and 25.0 Nm/radian respectively while derivative gains were 0.04 N/mm/s and 0.5 N/radian/s for translation and rotation respectively. Dithering distance for conical elements was 40% of element spacing.

- Experiment Subjects
 - 10 Male, 7 Female

- 15 Right-handed, 2 Left-Handed
- Conical Element Dimensions
 - $el_h = 0.42$ mm
 - $R_{top} = 0.23$ mm
 - $R_{base} = 0.52$ mm
 - $\alpha = 53^\circ$
- Stick-Slip (k_{Hay}) Friction Levels [N/mm]
 - [0.0, 0.5, 1.0, 1.5]
- Hayward Friction $Z_{max} = 1.4$ mm
- Hayward Friction $Z_{stick} = 2.0$ mm
- Viscous Friction Levels [N/mm/s]
 - [0.04, 0.06]
- 5 Demonstration Element Periods [mm]
 - [0.50, 1.50, 2.50, 3.50, 5.50]
- 10 Experiment Element Periods [mm]
 - [0.50, 0.75, 1.00, 1.50, 2.00, 2.50, 3.00, 3.50, 4.50, 5.50]

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