Assessing the Perceived Realism of Kinesthetic Haptic Renderings Under Parameter Variations

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***Abstract*— Despite the large amount of research on kinesthetic haptic devices and haptic effect modeling, there is limited work assessing the perceived realism of kinesthetic model renderings. Identifying the impact of haptic effect parameters in perceived realism can help to inform the required accuracy of kinesthetic renderings. In this work, we model common kinesthetic haptic effects and evaluate the perceived realism of varying model parameters via a user study. Our results suggest that parameter accuracy requirements to achieve realistic ratings vary depending on the specific haptic parameter.**

I. INTRODUCTION

It is generally challenging to render accurate kinesthetic haptic effects. For example, stiff virtual objects are difficult to render due to limitations of force-feedback (i.e., impedance) devices [1] and renderings involving a large number of parameters present challenges in accurate system identification [2]. As researchers continue to advance methods and systems to produce more accurate haptic renderings, it is also important to consider whether the improved accuracy benefits the perceived realism of the rendering. Studying perceived realism can inform the required accuracy and performance of haptic systems. Furthermore, understanding the sensitivities of users to imperfections in model parameters can help system designers balance tradeoffs during haptic actuator design.

While researchers have identified the dominant characteristics that can be used to assess the realism of virtual haptic textures [3], there is limited work investigating perceived realism of kinesthetic haptic renderings. Prior work, summarized in Section II, has primarily focused on magnitude estimation of haptic effects [4], [5] or a limited number of user realism ratings [6]–[8]. In this work, we are specifically interested in collecting a range of realism ratings to understand trends in perceived realism which can inform required accuracy for kinesthetic haptic displays.

In this work, we investigated the effect of parameter variations on perceived realism (i.e., the similarity of a rendering compared to the corresponding tangible object) for a common set of kinesthetic haptic effects. We identified and modeled a set of four objects which are comprised of these effects and developed an experimental apparatus for users to interact with and compare haptic displays alongside the corresponding physical objects. Finally, we conducted a user study where participants interacted with a range of model parameters for each of the objects and provided corresponding realism ratings. Our results indicate that sensitivity in perceived realism varies depending on the specific haptic parameter.

II. RELATED WORK

Our work focuses on evaluating realism ratings across a range of kinesthetic haptic effects and parameter variations. To contextualize our contribution, we present a brief review of previous work in assessing the realism of kinesthetic models of physical objects as well as studies on perceptual importance in haptic rendering.

A. Kinesthetic Modeling of Physical Objects

There are limited works which aim to model and assess physical objects with kinesthetic haptic displays. Shin et al. [6] simulated a refrigerator door by modeling the dynamics of the physical components of the door. In a user study, participants were prompted to provide realism ratings for only the most realistic and one other set of model parameters. Colton and Hollerbach [7], [9] used position and direction-dependent non-linear impedance models to simulate non-linear haptic behaviors such as buttons, switches, and turn signals. However, the subsequent user study focused on assessing settings in the proposed algorithm rather than the quality of the renderings. Swindells et. al. [8] compared human tuning to automated system identification for a four-parameter knob model. Participants were only asked to rate the similarity of the final tuning. As noted above, while some methods collected a small set of realism rating from participants, the data is insufficient to uncover trends in how participants perceived the realism of particular haptic effects.

B. Perceptual Importance of Rendering Elements

Existing works in haptic perception focus either on the effects of parameter variation on the magnitude of physical quantities (e.g., friction, hardness) or realism in vibrotactile surface renderings. Lim et. al. [5] assessed the importance of three parameters in a Dahl model in the magnitude estimation of friction rendering. Higashi et. al. [4] studied the relative importance of damped natural vibrations parameters in rendering hardness by varying individual parameters. Culberston and Kuchenbecker [10] investigated the relative importance of three haptic components (physical friction, hardness, and texture) when rendering surfaces on a touchscreen using leave-one-out cross validation. In our work, we follow a

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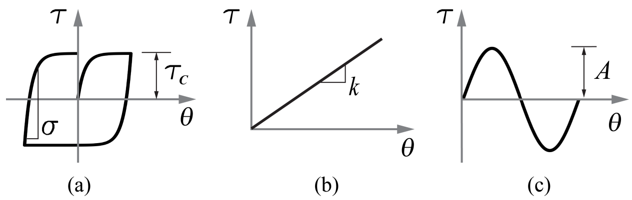

Fig. 1. Haptic rendering models: (a) Dahl friction model, (b) Linear stiffness model, (c) Sinusoidal detent model

similar procedure to the above works and vary individual parameters to assess the impact of individual parameters on realism of kinesthetic renderings.

III. Haptic Effects and Models

To understand how the accuracy of model parameters impacts perception of realism, we investigated three common haptic effects: friction, stiffness, and detents. In this section, we identify and define haptic models corresponding to each effect.

A. Friction

While there are many proposed friction models in the literature, the Dahl model is commonly used for haptic rendering because of its smooth force output around zero velocity [11]. The Dahl friction model, shown in Figure 1 (a), is defined as:

$$\frac{d\tau}{d\theta} = \sigma(1 - \frac{\tau}{\tau_c} sgn(\omega))^{\alpha} \tag{1}$$

where θ is the angular displacement, ω is the angular velocity, τ is the output torque, α defines the shape of the hysteresis loop, τ_c is the steady-state friction, and σ is the initial stiffness. Using backwards Euler differentiation and setting $\alpha = 1$, the Dahl model can also be expressed in discrete form for use in haptic renderings [11]:

$$\tau_{i+1} = \frac{\tau_i + \sigma\omega_i}{1 + \dfrac{\sigma\omega_i sgn(\omega_i)}{\tau_c}} \tag{2}$$

where $\omega_i = \theta_{i+1} - \theta_i$.

B. Stiffness

In general, the stiffness of objects exhibits some degree of nonlinearity, however, a linear model is frequently used in modeling for simplicity (e.g. programming, stability analysis). A linear stiffness model, shown in Figure 1 (b), can be expressed as:

$$\tau = k\theta \tag{3}$$

where k represents the linear stiffness. For objects involving a larger degree of nonlinearity, it is also possible to superimpose multiple linear stiffness models to describe the various regions of operation.

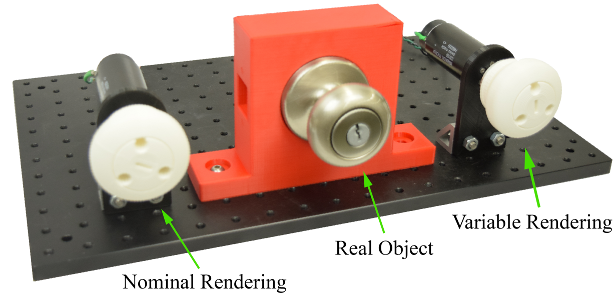

Fig. 2. Experiment apparatus

C. Detent

A detent, which is often colloquially described as a ”clicking” effect [12], is commonly modeled using a sinusoidal waveform [8], [13]. A continuous set of detents, shown in Figure 1 (c), can be modeled as:

$$\tau = A \sin f\theta \tag{4}$$

where A is the detent amplitude and f is the detent frequency which is measured in number of detents per revolution.

IV. Experiment

To study the perceptual importance of haptic model parameters, we performed a user study. The procedure was approved by University of Wisconsin-Madison IRB 2020-0504.

A. Participants

We recruited 18 participants from the UW-Madison campus (8 male and 10 female, age 18 to 29, Mean = 22.9, STD = 3.64). Three participants were left-handed and 15 participants were right-handed. None of the participants identified having extensive experience with kinesthetic-based haptics. Participants were compensated at $15 per hour.

B. Apparatus

The testbed, shown in Figure 2, consisted of the real object and two haptic rendering interfaces. Each of the interfaces consisted of a Maxon RE 35 brushed DC motor with a 1024 CPT encoder. The motor shaft was clamped to a 3D-printed handle that was geometrically similar to the physical object. A Speedgoat realtime controller[1] was used to render the effects and collect participants' data. The sampling rate of the system was 10 kHz. There was no visual interface included in the study.

C. Stimuli

We selected four real-world objects, shown in Figure 3, that could be simulated using the haptic models described in Section III and stably rendered by the experimental setup. In this section, we describe the stimuli provided to participants, including the objects and the haptic renderings.

[1]https://www.speedgoat.com

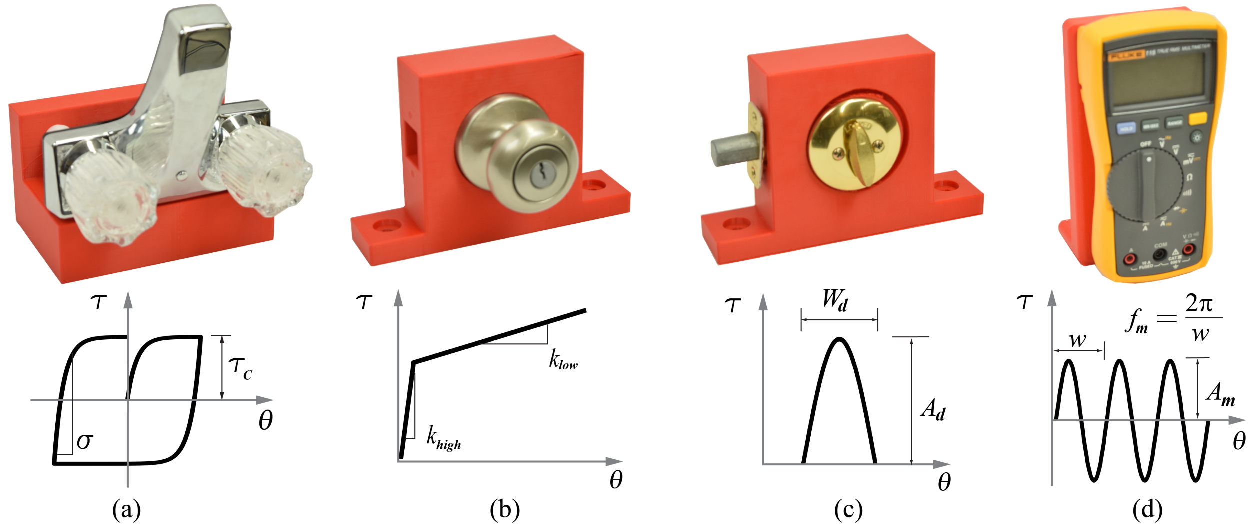

Fig. 3. Physical objects and their rendering models: (a) faucet knob with the Dahl model, (b) doorknob with linear stiffness model, (c) deadbolt lock with half sinusoidal model, (d) multimeter with continuous sinusoidal model

1) Physical Object Modeling: The faucet knob was rendered by the Dahl model with Equation 2. The parameters varied in the experiment were τ_c and σ, corresponding to the steady-state friction and the initial stiffness, respectively.

The doorknob was rendered by the stiffness model. The stiffness of the doorknob was much higher at small angles and thus the final model superimposes a low and high stiffness:

$$\tau = \begin{cases} k_{high}\theta, & \text{if } \theta \le \theta_s \\ k_{high}\theta_s + k_{low}\theta, & \text{otherwise} \end{cases} \quad (5)$$

The parameters varied for the experiment were k_{high}, the high stiffness for small rotations, and k_{low}, the additional lower stiffness that is rendered for larger rotations.

The deadbolt lock and the multimeter knob were both rendered using the detent model. The deadbolt lock contained only a single detent and thus used a half-sinusoidal model:

$$\tau = A_d \sin \frac{\pi\theta}{W_d} \quad (6)$$

The parameters varied during the experiment were A_d, the detent amplitude, and W_d, the detent width.

The multimeter knob, was rendered using the continuous detent model from Equation 4. The parameter varied for the experiment were A_m, the detent amplitude and f_m, the detent frequency as number of detents per revolution.

2) Haptic Renderings: During each experiment, one of the two available haptic interfaces displayed a variable haptic rendering of the object, where a single parameter of the rendering model was varied from an established nominal value. The other haptic interface consistently rendered the nominal value. We tested 11 evenly-spaced values for each parameter. The ranges of parameter variations needed for participants to report a range of realism values were informed by a pilot study [14] and were established such that the extremes of the range were perceived to be significantly less realistic than parameter values located more centrally.

The second haptic interface was used to present the participants with a nominal rendering as a reference for their realism ratings. The parameters of the nominal renderings were collaboratively determined based on a voting procedure among four haptic experts including the first author of this paper. The nominal renderings were consistent between trials. As the limits of the renderings were informed by realism ratings in the pilot study, the established nominal renderings were not generally located in the center of parameter range.

D. Procedure

To minimize the impact of participant fatigue, each individual interacted with two of the four objects (counterbalanced across participants). The participant sat at a table in front of the test bed and wore headphones playing pink noise to remove auditory cues. They were instructed to interact with the interfaces using only their dominant hand comfortably as they would normally interact with the real object in daily life. They were also instructed to follow similar trajectories with each interface (e.g. range of motion, velocity) and to complete three full articulations prior to assigning a realism rating.

To guide ratings, the participants were informed that the nominal rendering on the left was collectively determined by a group of haptic experts and was thus a good haptic representation of the physical object. However, participants were also informed that the nominal value may not be perceived as the most realistic by participants. As such, participants were told that the nominal rendering corresponded to a score of 7 on a 10-point scale where 1 meant completely different and 10 meant almost identical. Based on this reference, the participants rated the similarity between each variable haptic rendering and the real object using the same 10-point scale.

For each model, participants first provided realism ratings for all variations of one parameter, while the other parameter

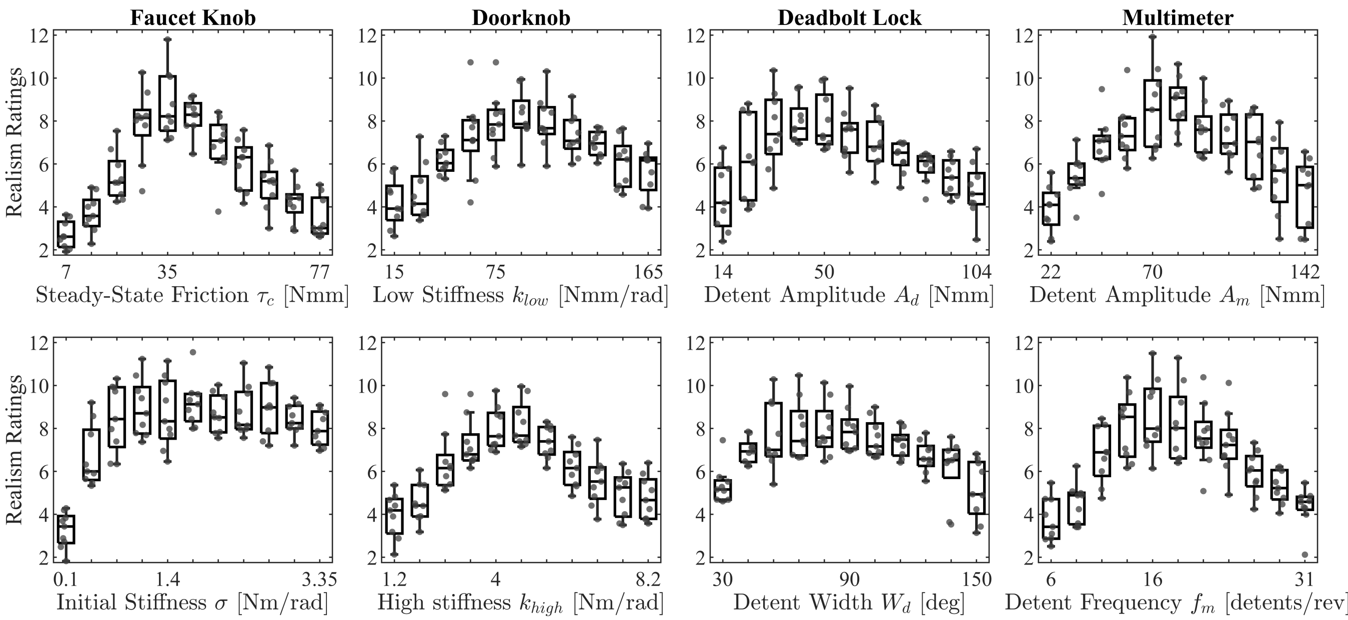

Fig. 4. Boxplots of normalized realism rating data. Individual data are overlaid (gray markers).

was kept constant at the nominal value. The order of the 11 parameter values were randomized. This rating process was repeated twice, with different permutations of the parameter values. Afterwards, participants repeated this process for the second model parameter. Participants were allowed a short break between objects as the experimenter switched the setup. Each participants completed a total of 132 trials (two objects, two parameters for each model, 11 parameter variations for each parameter, and three repetitions for each parameter value). Each session was designed to last an hour.

E. Data Analysis

Each participant's data was normalized geometrically. We ran a within-subject two-way ANOVA on the realism ratings, with parameter variation and repetition as the factors. The results from the ANOVA analysis, shown in Table I in the Appendix, confirmed that only parameter variation was a highly significant factor (p-value < 0.001) on the difference in realism for all parameters.

We calculated the average percent decrease in realism rating from the highest rating against the percent variation of parameter values, shown in Figure 5. We segmented each realism curve at the peak and fit separate power models to two segments, corresponding to decreases and increases to the parameter value which were generally asymmetric. A power model for one segment is defined as:

$$y = -cx^n \tag{7}$$

where x is the percent difference of the parameter value from the highest realism value, y is relative realism rating, calculated as percent decrease from the highest realism rating, c is the power-model coefficient, and n is the power-model exponent. The curve fits and corresponding values are shown in Figure 5. We also calculated the mean and standard deviation of the parameter values rated highest by participants (see the top error bars in Figure 5).

V. Discussion

We compared participants' highest-rated realism value for each haptic parameter. The range of parameter values varied across parameters, as shown in Figure 5. Certain parameters had a high level of consensus across participants, indicated by a low coefficient of variation (CV). For example, the detent amplitude and detent frequency of the multimeter had a CV of 0.0825 and 0.0885 respectively. Other parameters, such as the detent width of the deadbolt lock (CV: 0.300) and the initial Dahl stiffness of the faucet knob (CV: 0.495), had greater variability in the maximum-realism ratings. This may indicate that certain model parameters require personalization to achieve high realism ratings.

The power-model fits of the realism data provide intuition into the sensitivity of the haptic model parameters. As a reminder, each parameter has two fits corresponding to the asymmetric decrease and increase curves, which are denoted with subscript d and i respectively. To look for specific trends, we clustered the fits based on the coefficient and exponent of the power-model fit (i.e., c, n). From this process, we identified four groups which can be principally described by differences in the power-model exponent, n (see Figure 6 in the Appendix).

The first cluster was fits where the decrease in realism was approximately linear (i.e., $n \approx 1$). For example, the steady-state friction of the faucet knob (n_d = 1.06 and n_i = 0.999) and parameter increases of the multimeter detent amplitude (n_i = 1.02) ratings followed a near-linear trend. This behavior indicates that participants were equally sensitive to parameter changes across the range of parameter values.

The second cluster was fits where the decrease in realism was weakly quadratic (i.e., $1.32 \leq n \leq 1.99$). The majority

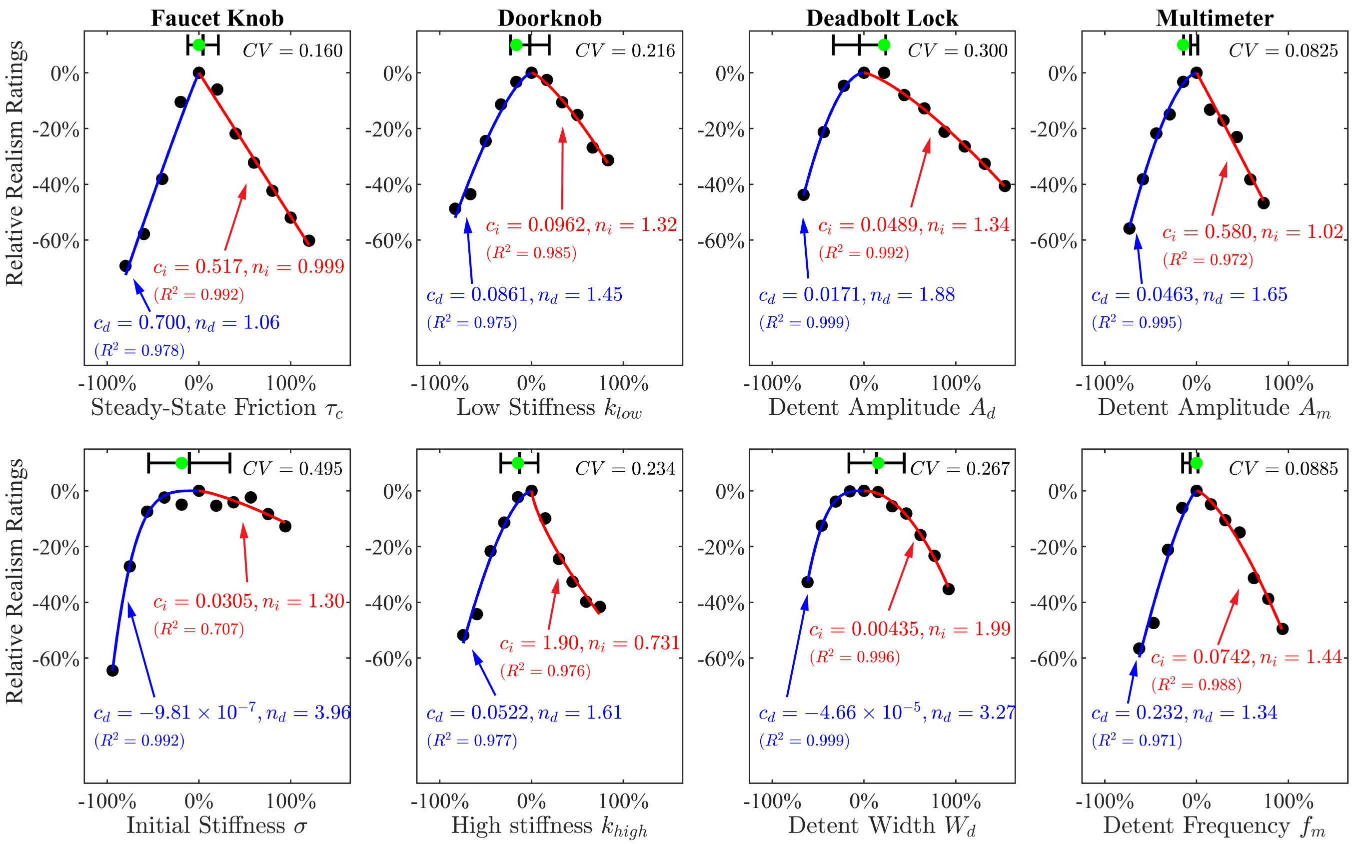

Fig. 5. Power fits for averaged decrease in realism with respect to percent parameter variation. The error bars show the mean and standard deviation of the highest-realism rating by participants. The nominal values are denoted by green dots.

of fits exhibited this behavior, including the low stiffness of the doorknob (n_d = 1.45 and n_i = 1.32), parameter decreases of the doorknob high stiffness (n_d = 1.61), the detent amplitude of the deadbolt lock (n_d = 1.88 and n_i = 1.34), parameter decreases of the multimeter detent amplitude (n_d = 1.65), the multimeter detent frequency (n_d = 1.34 and n_i = 1.44), and parameter increases of the deadbolt lock detent width (n_i = 1.99). Compared to the constant slope of linear behavior, the slope of a quadratic behavior is smaller around zero and grows as the value further deviates. This trend suggests that for these parameters, some inaccuracy in the model parameter may not have a large impact on users' perceived realism.

The third cluster was fits where the decrease in realism had a higher-order exponent in the power model (i.e., $n > 3.27$). This cluster consisted of parameter decreases of the deadbolt lock detent width (n_d = 3.27) and parameter decreases of the initial stiffness of the faucet knob (n_d = 3.96). The higher-order exponent indicates that a larger range of parameter values near the nominal are perceived as similarly realistic and thus, designers may not need to focus on fine tuning these parameters.

The final cluster was fits where the power-model exponent was less than one. In our experiment, this behavior only occurred when increasing the high stiffness of the doorknob (n_i = 0.731). We believe this may have resulted from imperfections in the high-stiffness rendering. The nominal value of the high stiffness was close to the rendering limit of the device and thus, increases in the parameter resulted in some instability. During the experiment, we observed that some participants noted vibrations from instability. Parameters with similar fits are susceptible to large decreases in perceived realism for small parameter changes and thus may require fine tuning.

One of the parameter-increase fits, the Dahl stiffness of the faucet knob, was not well explained by the power-model regression ($R^2 = 0.707$). We believe that this effect was more subtle compared to the other investigated effects and thus was only perceived at extreme values (e.g., very low values where the stiffness impacts perception of the steady-state friction). In the future, we plan to further explore such parameter interactions.

We also noted variation depending on the context of the haptic effect. For example, the detent width of the deadbolt lock and the detent frequency of the multimeter exhibited different trends in perceived realism which may imply that the trends are object specific. However, there were also confounding factors which may have contributed to the variation such as the number of detents and unit of the parameter (i.e., frequency vs width). In the future, we plan to isolate these effects to further explore the impact of specific objects and contexts.

VI. Conclusions

We varied kinesthetic haptic model parameters and measured participants' perception of realism to understand their sensitivities to the parameters. The results suggest that changes to the perceived realism are dependent on the haptic property that is varied. The specific results can provide insight for haptic device design and for the required accuracy of model parameters.

Limitations and Future Work – The findings may only apply to the specific effects rendered by the single DOF kinesthetic haptic device in this work. Other haptic effects (e.g. inertia) or other devices (higher DOF) may result in different sensitivities to parameter variations.

The rendering capability of the device set a limit on the upper limit of parameter variation that could be studied, such as the initial stiffness of the faucet knob and the high stiffness of the doorknob. The encoder resolution, velocity filtering and sampling frequency limited the stability and dynamic range of renderings [15]. For example, these factors may have impacted the rendering quality of the Dahl model at low velocities, which may have impacted realism ratings.

Future work will focus on examining a wider range of objects and haptic rendering effects. In addition, we plan to investigate parameter interaction (i.e. varying multiple parameters each time) to further understand human sensitivity to rendering parameters.

VII. Acknowledgement

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VIII. Appendix

TABLE I

ANOVA results on the realism data with repetition and parameter variation as the factors (* for p-value < 0.05, ** for p-value < 0.01, *** for p-value < 0.001)

Param	Repetition		Param Variation	
	$F(2,16)$	p	$F(10,80)$	p
τ_c	4.519	0.0278 *	28.6	$< 2 \times 10^{-16}$ ***
σ	1.605	0.232	27.6	$< 2 \times 10^{-16}$ ***
k_{low}	0.142	0.869	11.16	1.13×10^{-11} ***
k_{high}	0.263	0.772	15.95	2.52×10^{-15} ***
A	1.178	0.333	8.335	4.02×10^{-9} ***
W	1.135	0.346	7.591	2.17×10^{-8} ***
A	0.811	0.462	11.35	7.78×10^{-12} ***
f	0.182	0.836	16.05	2.15×10^{-15} ***

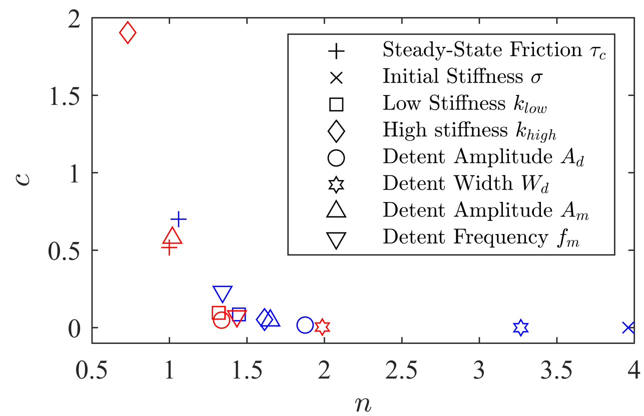

Fig. 6. Plot of the power-model coefficient and exponent for each model parameter which was used to cluster the parameter fits. The blue corresponds to parameter decreases and red corresponds to parameter increases. The parameter increase of initial stiffness was excluded due to a low coefficient of determination ($R^2 = 0.707$). As can be seen in the logarithmic shape of the curve, the values of c and n were generally dependent (i.e., c was a scaling factor which restored the normalized percentage range). Thus, we report clusters based solely on n.

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