Designing for Feel: Contrasts between Human and Automated Parametric Capture of Knob Physics

Colin Swindells, *Member*, *IEEE*, Karon E. MacLean, *Senior Member*, *IEEE*, and Kellogg S. Booth

Abstract—We examine a crucial aspect of a tool intended to support designing for feel: the ability of an objective physical-model identification method to capture perceptually relevant parameters, relative to human identification performance. The feel of manual controls, such as knobs, sliders, and buttons, becomes critical when these controls are used in certain settings. Appropriate feel enables designers to create consistent control behaviors that lead to improved usability and safety. For example, a heavy knob with stiff detents for a power plant boiler setting may afford better feedback and safer operations, whereas subtle detents in an automobile radio volume knob may afford improved ergonomics and driver attention to the road. To assess the quality of our identification method, we compared previously reported automated model captures for five real mechanical reference knobs with captures by novice and expert human participants who were asked to adjust four parameters of a rendered knob model to match the feel of each reference knob. Participants indicated their satisfaction with the matches their renderings produced. We observed similar relative inertia, friction, detent strength, and detent spacing parameterizations by human experts and our automatic estimation methods. Qualitative results provided insight on users' strategies and confidence. While experts (but not novices) were better able to ascertain an underlying model in the presence of unmodeled dynamics, the objective algorithm outperformed all humans when an appropriate physical model was used. Our studies demonstrate that automated model identification can capture knob dynamics as perceived by a human, and they also establish limits to that ability; they comprise a step towards pragmatic design guidelines for embedded physical interfaces in which methodological expedience is informed by human perceptual requirements.

Index Terms—Haptic I/O, evaluation/methodology, human factors, software psychology.

1 Introduction

The feel of the physical control handles we encounter throughout our environment influences both an interface's usability and the pleasure we take in using it. A knob or slider with inadequate damping, or detents that are too stiff, make precise positioning difficult; industrial designers have long known that the feel of a stereo knob or of a car door's closing affects the user's assessment of durability, quality, and appeal [8]. Good design considers both performance and aesthetic metrics.

A model that can be rapidly manipulated and tested with users facilitates designing for feel. One approach is to capture key characteristics of a real physical control handle, render those characteristics on a haptic display, and then manipulate them to achieve the desired characteristics, either for active display or reproduction in a mechanically passive device. A minimal requirement for this scheme to work is that the model and its rendering capture perceptually relevant elements—those allowing users to recognize the feel, use it, and form subjective responses that are qualitatively and quantitatively the same as the rendering's target.

There are several ways in which a haptically rendered model may fail to adequately capture its target. These may occur in either the *rendering* or *capturing* stage, with coupling possible. Choi and Tan [2] use the term "perceived instability" to describe an example of how poor haptic *rendering* quality can undermine subjective user experience, with an undesired layer of small vibrations overlaid on the intended model, analogous in some ways to an interactive graphical model displayed at too low a frame rate. Some haptic model forms or parameterizations are particularly subject to this instability. There are many other possible rendering inadequacies, stemming from physical limitations such as torque saturation and bandwidth, linkage nonlinearities and compliance.

Another problem is the failure to *capture* model details that are perceptually important, just as a set of underexposed photographs would be an inadequate medium for assessing subjective responses to a set of master paintings: the representation fails to transmit key visual details that would dominate a person's reaction if viewing the artwork first-hand. This might occur even when the model is generally appropriate, but has been inaccurately parameterized. When we use a mechanically passive user interface as a start or end point for a design cycle, this need for perceptually relevant fidelity applies to initial capture and final manufacturing specifications as well as to the design cycle itself.

- *C. Swindells is with the Department of Computer Science, University of Victoria, 3800 Finnerty Road, Victoria, BC, Canada V8P 5C2. E-mail: colin.swindells@gmail.com.*
- *K.E. MacLean and K.S. Booth are with the Department of Computer Science, University of British Columbia, 201-2366 Main Mall, Vancouver, BC, Canada V6T 1Z4. E-mail: {maclean, ksbooth}@cs.ubc.ca.*

Manuscript received 15 Nov. 2008; revised 19 Mar. 2009; accepted 12 Apr. 2009; published online 21 May 2009.
Recommended for acceptance by K. Kahol, V. Hayward, and S. Brewster.
For information on obtaining reprints of this article, please send e-mail to: toh@computer.org, and reference IEEECS Log Number THSI-2008-11-0085.
Digital Object Identifier no. 10.1109/ToH.2009.23.

In this paper, we describe an experiment devised to validate an algorithm for model capture and rendering described in Swindells and MacLean [16], by comparing that algorithm's objective identification of model parameters for real knobs with users' own characterizations. For the types of systems we consider here, it is helpful to use an analogy with visual image processing. We might validate the efficacy of an automated color model *capture* by first asking a viewer to manually adjust an image's brightness, hue, and contrast to match that of the real scene it represented, then compare these levels with automated characterizations of the same variables. Conversely, we might validate *rendering* efficacy by asking viewers to compare an image's colors on a computer display with an accepted standard such as the same image printed on a piece of paper. There are many possible variants on these basic ideas. The one employed here focuses on determining the *fidelity* offered by the algorithm and its rendering, relative to the user's direct perception (how closely the automatically captured model resembles one deemed a good match by the user), and by implication, *model relevance* (the degree to which the parameters employed can be tuned to match the user's perception).

Our previous rotary "Haptic Camera" work captured the "feel" of rotary physical controls [16]. Here, we deploy a user-based validation test on models captured using the "Haptic Camera" (see Fig. 4). These studies showed that parameterizations by our auto-generated second order force-feedback renderings are within the tolerances observed in classic user studies involving purely mechanical knobs such as those by Knowles and Sheridan [10] and Woodruff and Helson [18]. We conclude that our capture and rendering technique is adequate for the purpose of studying performance and eliciting a range of subjective responses for at least the range of systems examined here. Our results should be applicable to similar haptic manual controls such as sliders and buttons.

2 Approach and Background

Our Haptic Camera identification algorithm has been validated algorithmically by comparing capture of simulated systems with and without added noise [16], but this did not tell us whether the models themselves contained and faithfully reproduced the elements of "feel" on which human observers rely. Establishing this was the goal of the human-based validation reported here.

The experiment material was the five real (passive mechanical) reference knobs detailed in Table 1, which are describable primarily in terms of inertia, friction, and detents (1), together with their Haptic Camera parameterizations taken from [16]. We asked participants to match the "feel" of a haptic rendering to each of the real reference knobs, in turn, by adjusting the rendering's model parameters. Then, for each reference knob, we examined 1) the extent to which the human-generated parameterizations agreed with the automatically captured ones, implying parameter fidelity, and 2) participants' satisfaction with the fidelity of the renderings created by each set of parameters (human and automatic) to the target. A high degree of satisfaction should be linked to a subjectively effective degree of control over the rendering model, implying that the parameters being manipulated were the perceptually important ones and hence that the model was relevant.

TABLE 1
Descriptions of the Five Reference Knobs

Knob Label	Description *Original Source*
high friction	No detents, moderate friction, low inertia *High-end 1960's AM/FM radio volume*
high inertia	No detents, low friction, high inertia *High-end 1960's AM/FM radio tuning knob*
subtle detents	Subtle, consistent detents, low friction, 30 clicks/ 360° *Good quality 2004 automobile radio volume*
Moderate detents	Moderate, consistent detents, 12 clicks/ 360°, moderate friction, low inertia *High-end 1970's audio receiver source selection*
Non-sinusoidal detents	Wide non-sinusoidal, rough, regularly spaced detents, 12 clicks/360°, backlash, slip, moderate friction, low inertia *Good quality 2004 automobile fan settings*

Previous researchers have conducted expert versus novice experiments. For example, Forrest et al. [5] provide example haptic research comparing experts and novices for veterinarian training. While presumably experts and novices feel the same thing, experts are significantly more able to articulate and act upon their haptic perception of an underlying system when it occurs in clinically relevant settings. In line with such research, our studies include both novice and expert studies. Our expert study probes more deeply into the underlying physics of the haptic knob, whereas the novice study probes typical responses of average end users of physical controls.

We chose the rendering model shown in (1) for our experiment. The following sections describe how we considered human and machine capabilities to arrive at this model:

$$\tau = \mathrm{M_{acc}}\ddot{\theta} + \mathrm{B_{vel}}\dot{\theta} + \mathrm{A_{pos}}\sin\left(\frac{\theta}{\mathrm{P_{pos}}}\right), \tag{1}$$

where τ is the torque rendered by the force-feedback knob; $\theta, \dot{\theta}, \ddot{\theta}$ are measured knob position, velocity, and acceleration imposed by the user, respectively; $\mathrm{M_{acc}}$ is the acceleration constant used in captured knob model, intuitively close to inertia; $\mathrm{B_{vel}}$ is the damping constant, intuitively similar to friction; and $\mathrm{A_{pos}}, \mathrm{P_{pos}}$ are the amplitude and period parameters for detents, respectively.

2.1 A Human-Manageable Rendering Model

Our first challenge was to define a version of the experiment task (matching a rendered to a real knob by adjusting model parameters) by which it would be feasible for human participants to communicate their sense of how a moderately complex rendering should feel.

Recent research suggests that humans have a short-term memory capacity limit for managing simultaneous percepts that averages about four chunks of information [4]. This is a problem. A Karnopp friction model contains seven parameters and a sinusoidal detent model contains another

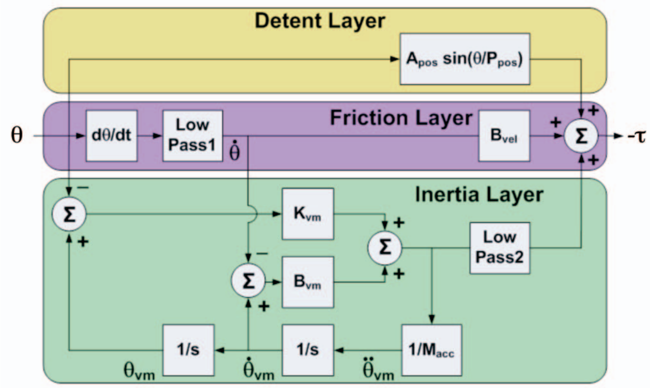

Fig. 1. Haptic knob rendering model.

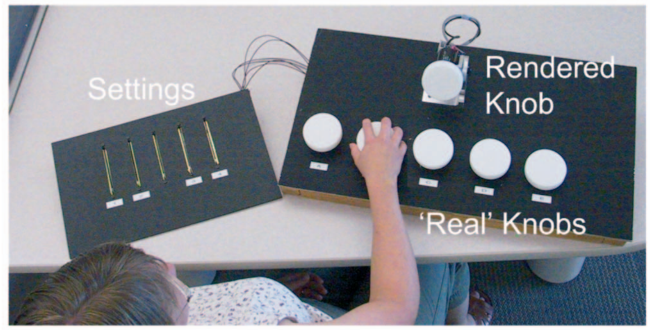

Fig. 2. Apparatus for "feel" matching experiments. The sliders (left) were used to adjust the four model parameters for the rendered haptic knob (upper right) to make the rendering match one of the real reference knobs (lower right), one at a time.

three parameters; our Haptic Camera capture model entailed, in all, eight parameters [16]. Clearly a normal human, even one with a good understanding of the model, would have difficulty managing this combined level of detail. We, therefore, sought ways to simplify the automated capture model to make it more accessible to human assessors, while still giving them control over perceptually important components.

Inertia can be effectively modeled from both machine and human perspectives, with a single-parameter virtual mass [3], [13]. The capture model's M_{acc} was retained as one of our user-adjusted free parameters.

We captured friction using a seven-parameter Karnopp model. In previous characterization research such as Richard [13], the stick-slip boundaries (C_{vel-} and C_{vel+}) and damping components (B_{vel-} and B_{vel+}) of a Karnopp friction model were discovered to be the most perceptually relevant. In pilot studies, we found that users instructed to adjust a full Karnopp model to match a reference knob struggled to discern exact stick-slip boundaries and that stick-slip rendering values impacted the feel of other rendered parameters. Therefore, assuming symmetry and steady velocity, we combined these four velocity-related components into a single symmetric damping constant (B_{vel}) to achieve an independent, linear control over model dissipation, which was fairly consistent with the friction feel in the reference knobs.

The detent capture model consisted of detent frequency, amplitude, and phase shift. However, because our three reference knobs that contain detents had fairly high detent frequencies of at least 12 detents per revolution, detent phase shift was not perceptually relevant. We thus asked users to adjust only frequency and amplitude.

Together, these simplifications left us with four free parameters we believed to be perceptually influential (one inertia, one friction, and two detent)—a number that lies within Cowan's recommended upper bound of five for the number of simultaneously manageable percepts [4].

2.2 Choosing a Rendering Model

Fig. 1 shows the rendering model used to generate torques on the haptic knob shown in Fig. 2. The model is visually organized into three layers to illustrate the three intuitive components—detents, friction, and inertia terms—similar to the model used during the capture of mechanical knob dynamics [16].

The model components are:

- *Detent Layer*: It is a sinusoidal model for detents that varies in amplitude and frequency.
- *Friction Layer*: It is a damping constant corresponding to the "slip" state of the Karnopp capture model.
- *Inertia Layer*: It is based on a virtual mass [19]. This submodel employs compliance and damping elements for stable control; two of the parameters were fixed at conservative values of $K_{vm} = 12{,}000$ Nm/rad and $B_{vm} = 88$ Nm/rad/s for user trials.
- *"Low Pass 1"*: It is a 10th order Butterworth IIR low-pass filter with a passband edge of 400 Hz and ripple of 3 dB, and a stopband edge of 700 Hz and attenuation of 50 dB (see Brouwer [1]).
- *"Low Pass 2"*: It is a filter for the virtual mass rendering consisting of box filtering of the last three updates.

2.3 Psychophysical Appropriateness of the Models

The models we used for haptic camera capture and subsequent rendering are similar to psychophysical models used by other researchers to describe kinematic movement of a person's hand during a rotation task. Our model describes the dynamics of a physical control, not of the user's hand. However, we argue that if our knob model encompasses high-quality models of hand dynamics, it can potentially feel perceptually complete.

Equation (2) is a nonlinear mass-spring model of movement used by Novak et al. [12] to describe rapid hand movement experimentation with a passive rotary control. Novak et al.'s model represents typical human wrist motion and is applicable for describing complicated finger and wrist turning motions associated with knob turning tasks. Our model (refer to (1)) omitted the exponent of 0.2 in the damping term because its exact value is disputed (see Novak et al.'s related work [12]).

$$\tau = M_{acc}\ddot{\theta} + B_{vel}\dot{\theta}^{0.2} + K_{pos}(\theta - \theta_{eq}), \tag{2}$$

where τ is the torque rendered by the force-feedback knob in studies described in this paper, composed of position, velocity, and acceleration components; $\theta, \dot{\theta}, \ddot{\theta}$ are knob position, velocity, and acceleration, respectively; θ_{eq} is variable slack rotation of the wrist; M_{acc} is the acceleration constant, intuitively close to inertia; B_{vel} is the damping constant, intuitively similar to friction; K_{pos} is the positional spring constant, intuitively close to stiffness.

3 Methods and Procedures

We conducted a pair of user studies to clarify the relationships between automated and human characterizations of physical device dynamics. Specifically,

- What human responses to haptic properties can and cannot be accurately identified by an automatic (Haptic Camera) process?
- What aspects of haptic properties do people rely on when forming their percepts?
- What are relative strengths and weaknesses of automatic and human identification processes?

Participants adjusted model parameters rendered by our force-feedback knob to match the feel of the five real knobs of Table 1, one knob at a time. The first study employed novices with no particular knowledge of physical systems; the second employed experts with haptic training in mechanical systems and models.

3.1 Participants

We sampled from different populations in the two studies. We believe the *novices* in the first study represent a typical user's sensitivity and vernacular understanding of how detents, friction, and inertia feel. Experts were used in the second study to explore the bounds of human perception of mechanical control dynamics. We believe that experts have a heightened awareness of how underlying physics and mathematics change the feeling of detents, friction, and inertia, as well as the language to verbalize these percepts. For example, experts understand the differences between Karnopp and Stribeck friction models, understand that detents can be modeled with torque that is a sinusoidal function of position, and that inertia is a predominantly acceleration-dependent effect. Novices had to rely solely on their daily experiences with physical controls such as knobs, whereas experts also relied on their understanding of mechanics. Even if novices and experts were both able to create equally good mental models of a haptic behavior, experts would typically be able to more clearly articulate and describe their mental models.

Right-handed paid participants were recruited for a study lasting approximately one hour. Part 1 of the study employed 15 novices (10 female and 5 male) with ages ranging from 20-29 years ($M = 24.7, SD = 2.8$). Part 2 employed five experts (two female and three male) with ages ranging from 23-31 years ($M = 27.2, SD = 3.2$).

3.2 Matching Apparatus

Participants interacted with the apparatus shown in Fig. 2. By adjusting the four physical sliders (left), they changed the dynamics of a haptic knob rendering to match the dynamics of each of five real mechanical reference knobs (right), one at a time, to the best of their ability. The real knobs were labeled sequentially with letters A-E. The four physical sliders were sequentially labeled with numbers 1-4. Participants controlled the magnitudes of the four rendering parameters $M_{acc}, B_{vel}, A_{pos}$, and P_{pos} in (1), as applied to the current virtual knob rendering. Table 2 lists the minimum (bottom) and maximum (top) slider settings. Mappings were linear between the minimum and maximum values of M_{acc}, B_{vel}, and A_{pos}, but interpolated on $1/P_{pos}$ instead of P_{pos} to avoid unbounded extremes. Table 1 contains intuitive descriptions of the "feel" for each real knob.

TABLE 2
Slider Value Ranges

Slider	*Adjusted Parameter*	*Minimum → Maximum Values**
M_{acc}	Inertia	$0 \rightarrow .75$ mNm / rad/s^2
B_{vel}	Damping	$0 \rightarrow 30$ mNm / rad/s
A_{pos}	Detent ("click") amplitude	$0 \rightarrow 15$ mNm
P_{pos}	Detent ("click") spacing	$\infty \rightarrow 0.2$ rad ($0 \rightarrow 32$ detents / rev)

** These physical units map to standardized slider values 0→1 in Figure 6.*

As illustrated in Fig. 2, the physical sliders were visually grouped as one pair for M_{acc} and B_{vel}, and one pair for A_{pos} and P_{pos}, separated by an empty slot. The sliders for M_{acc} and B_{vel} independently controlled the inertia and friction, respectively, whereas A_{pos} and P_{pos} worked together to adjust the detents (2). The mechanical reference knobs were also organized according to this division. The high-friction (A) and high-inertia (B) knobs did not have detents, whereas the subtle-detent, moderate-detent, and nonsinusoidal-detent (C, D, and E) knobs did have detents. Sliders A_{pos} (3) and P_{pos} (4) were, therefore, not needed to model the high-friction and high-inertia knobs.

The small difference in height between the rendered knob and the row of real reference knobs was designed such that users could easily reach all knobs with minimal changes to overall posture. The height difference did result in a small alteration to participants' grasp angle for the knobs in either row. During the experiment, we watched for an influence of this difference on results. One expert volunteered that the angular differences between the haptic knob mounting and the reference knob mounting did not interfere with parameter estimation. This together with a lack of any other comments or observations of concern suggests a reasonable robustness of the data reported below to the physical layout of the knobs. The horizontal positioning of the automated capture equipment did not influence the experimental results because our capture algorithm employed a gravity compensation technique. Thus, gravity is not discussed for our human or automatic dynamic parameter results.

3.3 Force-Feedback Knob and Real Knob Models

The virtual models were displayed on a force-feedback knob which consisted of a DC motor, position sensor, and knob, illustrated in Fig. 3.

3.3.1 Force-Feedback Knob Description

The actuator was a Maxon RE40 #148867 DC motor capable of delivering 181 mNm of continuous torque. The position

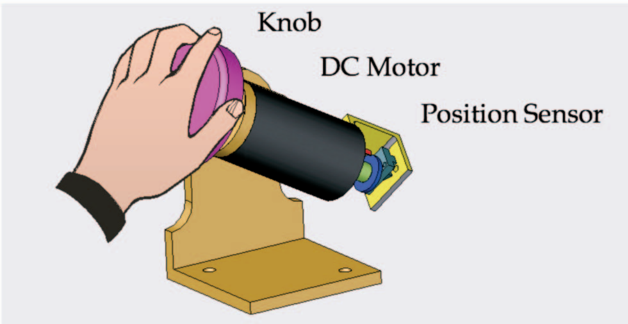

Fig. 3. Force-feedback knob setup for user studies.

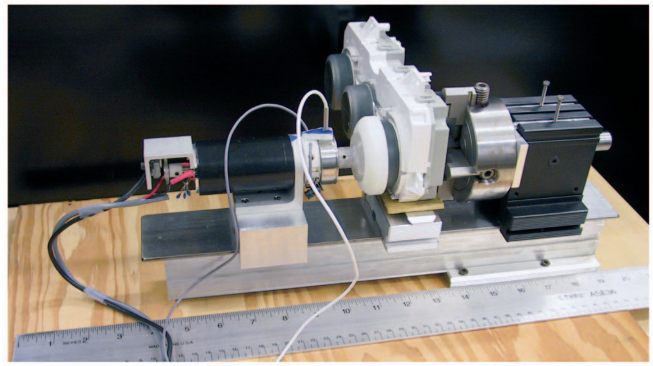

Fig. 4. Haptic camera for capturing the knob's model parameters.

sensor was a MicroE optical encoder with a 19.05 mm glass grating capable of 640,000 counts/revolution (0.00056 degree) accuracy. This knob was mounted to a stiff, machined aluminum holder.

3.3.2 Auditory Effects

Novice participants wore noise-canceling headphones that reduced or eliminated the sounds of clicks from the mechanical reference and rendered knobs. Because experts used a think-aloud protocol, we could not employ this mitigation measure with them and thus multimodal effects may have played some role in the observed results. If present, its impact would be limited to the detent knobs. The primary impact would be undesired cues in accurately matching detent frequency.

3.3.3 Force-Feedback Knob Rendering Capability

The haptic knob delivers 181 mNm of continuous torque at a 5,000 Hz update rate. Excluding commanded renderings, the haptic knob motor had negligible viscous friction and very low Coulomb-type friction from the commutator brushes that was probably felt but overshadowed by the model damping parameter, B_{vel}. The motor had a low inertia of $134\ gcm^2$; the cap and encoder of the haptic knob had inertias of $25\ gcm^2$ and $1\ gcm^2$, respectively. The knob had small maximum axial and radial plays of 0.10 and 0.025 mm, respectively.

Subjectively, the detents and damping had low perceived instability [2] with no unmodeled jitter or activeness. At high-inertia settings, the spring constant for the virtual mass, K_{vm}, could be felt in making rapid motions. The inertia rendering introduced a perceived instability that felt like a rough texture of a few mNm in magnitude; however, this texture felt similar for all slider settings.

3.3.4 Capturing and Modeling Model Parameters

Haptic models of the five test knobs were captured using the Haptic Camera apparatus (Fig. 4) developed by Swindells and MacLean [16]. The knob modeling process consisted of 1) exciting the knobs with precisely controlled swept-sine kinematic and torque trajectories while measuring torque and kinematics, respectively, then 2) estimating second order model parameters using a nonlinear least squares fit (Matlab's *lsqcurvefit* and \ commands [6]).

Table 3 shows the capture resolutions from the Haptic Camera. Position and velocity resolutions are from a MicroE M2000-M05-256-4-R1910-HA optical encoder; acceleration resolutions are from an Analog Devices ADXL 202 accelerometer; and torques were measured using a Honeywell-Sensotec QWFK-8M strain gauge.

3.4 Qualitative Evaluation

For the qualitative aspect of both studies, participants were given sticky notes and a pen, then asked to label the sliders with descriptive keywords.

All knobs had identical smooth, white, unmarked ABS plastic caps measuring 70 mm in diameter and 16.5 mm in depth, with a 3 mm edge fillet. Reference knobs (Table 1) were organized in a row beneath the rendered knob. Identical caps ensured participants compared only dynamic knob properties, not textural surface properties on the control handle. Exposing participants to the surface textures of the reference knobs would have introduced additional haptic noise and visual multimodal effects.

Disguising the identity of the rendered haptic knob from the participants could potentially prevent participants from being influenced by their preconceived biases toward either an active knob or a passive reference knob. However, in this case, such an attempt would have been futile even with perfect rendering: participants would readily determine the identity of the rendered knob within a set of passive reference knobs as the one whose dynamics changed in response to physical slider settings.

3.5 Procedure

The experimenter manually reset the physical sliders to their off (bottom) positions at the beginning of each session and individual trial. For both studies, each experiment session was carried out in two phases.

3.5.1 Familiarization Phase

Participants explored the effects of each slider on the rendered knob. They were first told to alter M_{acc}, then B_{vel}. Next, they were told to move A_{pos} and P_{pos} near the middle of each slider's range, and observe the effects of each

TABLE 3
Haptic Knob Capture Sensor Resolutions

Position	*Velocity*	*Acceleration*	*Torque*
9.8×10^{-6} rad	2.0×10^{-4} rad/s	2.8 rad/s^2	1.8×10^{-4} Nm

control slider. Participants repeated this until they felt comfortable and confident using the apparatus. They then wrote down their own keywords on sticky notes to describe each slider's effect on the rendered knob, and affixed the note beneath the appropriate physical slider.

Expert versus novice study. During this apparatus exploration phase, the experimenter verbally described the underlying physics (mass, damping, detent amplitude, and detent frequency) modified by each slider to the expert participants, but not to the novices. The experts were able to understand this explanation; explaining it in these terms rather than requiring them to find them by exploration allowed us to more quickly progress toward studying more interesting, subtle knob attributes.

In an effort to minimize participant bias, none of the participants were told whether the five reference knobs were passive or rendered; nor were specific inertia, friction, or detent properties of the five reference knobs discussed with any of the participants.

3.5.2 Test Phase

Novice study. Novices encountered the knobs in two groups—knobs without detents, followed by knobs with detents. The order of knobs was randomized within each subset and only the relevant sliders were used for each group ($\mathrm{M_{acc}}$ and $\mathrm{B_{vel}}$ for knobs without detents, and $\mathrm{M_{acc}}$, $\mathrm{B_{vel}}$, $\mathrm{A_{pos}}$, and $\mathrm{P_{pos}}$ for knobs with detents). This limit on randomization (always testing nondetent knobs before knobs with detents) was justified by the benefits in learning accrued from gradually increasing the task's cognitive load from two independent parameter adjustments to four parameters, two coupled. Compensating for cognitive load differences was deemed more important than the possible introduction of small memory biases. Novices were instructed to take as long as they desired (typically about two minutes per match) to adjust the $\mathrm{M_{acc}}$ and $\mathrm{B_{vel}}$ sliders to match each knob a total of three times. They first matched the two knobs without detents (high friction and high inertia) in some order, repeating the sequence three times. They then adjusted all four sliders to match the detent knobs (subtle detent, moderate detent, and nonsinusoidal detent) one after the other in some order, repeating the sequence three times.

For each repetition, the participant encountered a different randomized ordering of the target reference knobs. A trial consisted of using physical sliders to match the "feel" of the rendered knob to match the "feel" of a reference knob as closely as possible, then rating how similar these two knobs felt. For all trials, participants were instructed to rotate the knobs with their right (dominant) hand and to adjust the sliders with their left (nondominant) hand. This protocol was intended to avoid perceptual or cognitive differences related to right and left hand usage. After each trial, participants were asked to rate how satisfied they were with the match between the rendered knob (using the parameters they had adjusted) and the reference knob. Participants gave a rating between 1 for "strongly agree" and 9 for "strongly disagree" to the question, "I am satisfied with the match between the rendered and mechanical knobs."

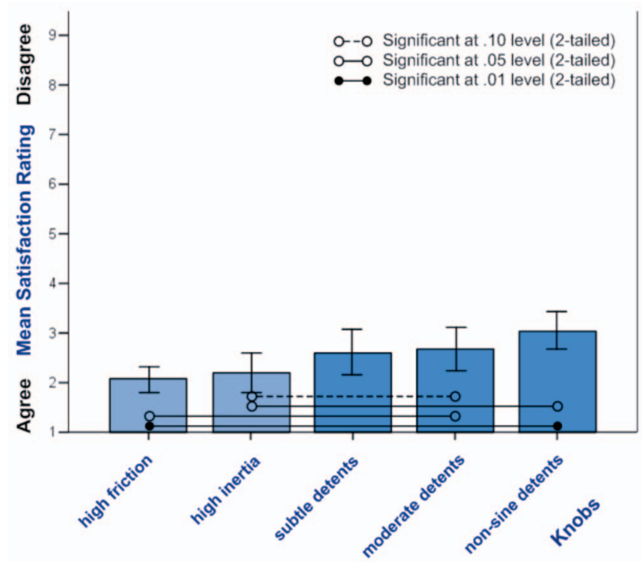

Fig. 5. Novice ratings of satisfaction for how closely each rendered knob matched its target mechanical test knob; lower scores correspond to better matches ("1" indicates a "strongly agree" satisfaction rating with the match).

Expert study. Experts followed the same procedure as the novices, except the experts were instructed to 1) adjust all four sliders regardless of which reference knob was being adjusted, 2) perform one very careful sequence consisting of a fully randomized ordering of the five reference knob trials, in lieu of three sets of rapid, repeated trials, and 3) verbalize their thoughts and strategies during the experiment in a think-aloud protocol. We felt it was appropriate to ask experts to perform only a single careful trial for each knob because being experts, they were less likely to benefit from learning about the knob models during the trials. Instead, they had extra time for exploration and verbalization. Adjusting all four sliders for all five reference knobs was not believed to be a burden because the experts were trained in mechanical systems and models, and they had more exploration time compared to novices. The experts' comments were transcribed by the experimenter for qualitative analysis (Section 5.3).

4 Results

Fig. 5 shows how satisfied novice participants were with how closely each of their final knob renderings matched each of the five reference knobs. Participants gave favorable satisfaction ratings for all knob renderings [$M = 2.5,\ SD = 1.0$]. Pairwise comparisons between the satisfaction ratings were performed using a standard nonparametric Wilcoxon Signed-Ranks test with Bonferroni correction. Significant differences were observed between the high-friction and nonsinusoidal-detent knobs [$Z = 2.58,\ p < 0.01$], the high-friction and moderate-detent knobs [$Z = 2.17,\ p < 0.03$], the high-inertia and nonsinusoidal-detent knobs [$Z = 2.43,\ p < 0.015$], and the high-inertia and moderate-detent knobs [$Z = 1.61,\ p < 0.01$].

Fig. 6 shows the relationships between settings for the five reference knobs when matched by expert participants,

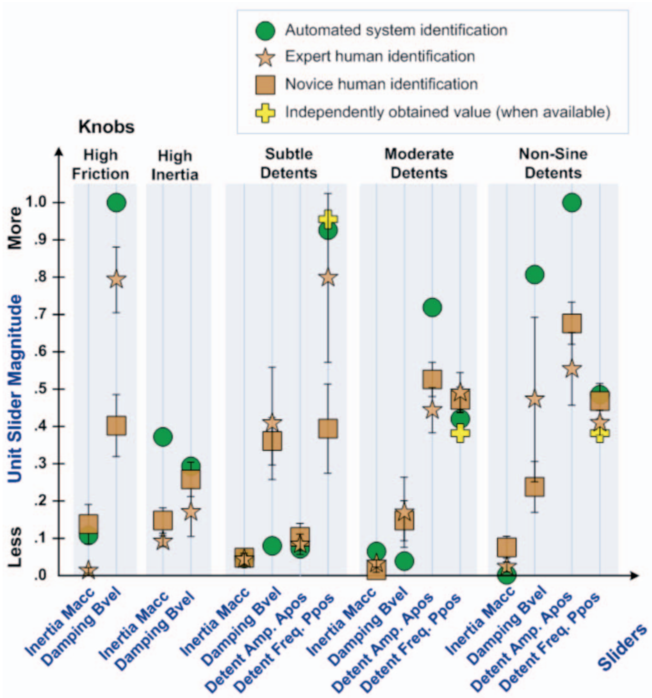

Fig. 6. Comparisons of expert, novice, and automated system identification characterizations for all five test knobs. Human characterizations were performed in clusters, setting only the parameters present in these knobs. Slider magnitudes for each adjusted parameter are listed in Table 2.

novice participants, and the automated Haptic Camera characterization process. To better compare participant slider settings, the dependent axis of Fig. 6 is scaled to the minimum and maximum stable operating levels for the rendered knob (Table 2). Error bars ($\alpha = 0.05$) are shown for expert and novice participants. Error bars were not calculated for the automated system identification (Haptic Camera) values because only two independent captures were obtained; however, 95 percent confidence bounds for the overall torques are listed in Table 4. Error bars are also not displayed for the independently obtained values for A_{pos} because they are, by definition, error-free perfect data determined by counting the number of clicks per 360 degree (this is explained below).

The two leftmost shaded columns of Fig. 6 display slider settings for the two knobs without detents, and the three rightmost shaded columns display slider settings for the

TABLE 4
95 Percent Confidence Bounds for Two Independent Captures of "Feel" Using Automated System Identification of Torques for the Five Test Knobs

Knob *95% CI for*	*High Friction*	*High Inertia*	*Subtle Detents*	*Moderate Detents*	*Non-Sine detents*
Capture 1 (mNm)	±0.26	±0.18	±0.098	±0.073	±3.3
Capture 2 (mNm)	±0.35	±0.20	±0.084	±0.072	±5.1
Quality	*Good*	*Good*	*Very Good*	*Very Good*	*Poor*

TABLE 5
Detent Estimates for Knobs with Detents (Percent Error Compared to Independent Estimate)

Knob *detents/rev (% error)*	*Subtle Detents*	*Moderate Detents*	*Non-sine Detents*
Gold-Standard	30	12	12
Haptic Camera	29.1 (3.0%)	13.2 (10.0%)	15.2 (26.7%)
Human Expert Adjusted	25.1 (16.3%)	15.4 (28.3%)	12.9 (7.5%)

three knobs with detents. Columns of detent amplitude, A_{pos}, and period, P_{pos}, data are shown only for knobs with detents because these parameters are not relevant for knobs without detents.

For the special case of detent frequency (period), independently obtained "gold-standard" values can be easily calculated by counting the number of clicks while manually turning the knobs with detents about one complete revolution. The number of clicks was also validated using visual inspection for the moderate-detent and nonsinusoidal-detent knobs. Visual confirmation was not performed for the subtle-detent knob because the confirmation could not be performed without permanently disassembling the mechanical knob subcomponents. Table 5 lists the gold-standard values for these knobs beside the values obtained by the Haptic Camera and expert participants. We note here that because the knob caps were unmarked, users could not easily count clicks per revolution, an aid that might have brought their performance closer to that of the Haptic Camera (which *did* benefit from position data).

Gold-standard values for inertia on real knobs were difficult to obtain because of the need for a complicated physical model. Friction gold standards are even more problematic, requiring surface material and geometrical properties between all moving parts. Calculating stick-slip friction also impedes independent estimation of detent amplitudes. One would need to first calculate the geometries and material properties of the detents, then estimate the reaction torques generated as a user rotates through the detent. These alternative estimation methods are too tedious and error-prone to be relied upon.

Table 6 lists the terms that each of the 15 novices recorded on their sticky notes about the sliders. Data from experts are not described because slider settings were explained to the expert participants, so results of their sticky notes might be biased. Each participant used one sticky note for each of the four model parameters.

5 Discussion

Our study's goal was to accurately compare human and machine model characterizations, and thereby infer whether our system-identification and rendering models are accurately capturing and displaying perceptually relevant attributes of real manual controls.

One metric of capture adequacy is the accuracy with which the identification algorithm fitted data to the model; this is examined in Section 5.1. However, even a perfect fit

TABLE 6
Novice Participant Tags for Knob Parameters
(Rows Correspond to Participants)

Part.	M_{acc}	B_{vel}	A_{pos}	P_{pos}
P1	Weight, "whoosh"	Friction, heavy	Bigness of detents	How many detents
P2	Spinny	Stiffer, like moving through mud	Really bumpy	Small bumps, big bumps for fine tuning
P3	Spin faster	Spin slower and stops	Feeling bumps	Spacing bumps
P4	Rotational force control	Friction force control	Control for a cycle of rotation	Smoothness of rotation controls
P5	Weight	Friction	Bump height	# of bumps
P6	Increase resistances, no brake	Increase resistance, + brake	Increase stage effect	Decrease stage width
P7	Smooth, but heavy	Light and smooth, buttery	Turning a smooth knob in definite steps	Turning a knob with shorter steps in between
P8	Spin automatically	Less resistant	Clicks	Faster
P9	More friction	More friction, feels better than 1 [M_{acc}]	More cranky	Cranky
P10	Momentum	Pudding	Bump size	Bump frequency
P11	Resistant spin	Smooth spin	Wobbly	Knobbly
P12	Slingy	Hard to turn	Big clicky	Clicky
P13	Resistance	Sensitivity	Smoothness	Ditto (smoothness)
P14	Easy, little bumpy	Touch, sticky, but smooth	Stiff, large bumps	Less stiff, smaller bumps
P15	Inertia	Velocity control	Amplitude of detents	Frequency of detents

will not serve if the model itself does not include perceptually relevant attributes of knob properties. Haptic Camera and human estimates must, therefore, be considered together if we are to understand how well the "feel" of the reference knobs (from the human perspective) were captured and rendered.

To this end, the rest of our discussion has three parts. In Section 5.2, we *quantitatively* compare haptic matching results (i.e., parameterizations) between the Haptic Camera and human assessors. In a *qualitative* data analysis, we seek to provide a deeper understanding of the objective results. In Section 5.3, we use novice participants' sticky note memory aids to deduce ability to recognize dynamic knob properties. Finally, in Section 5.4, we distill more nuanced perceptual attributes of knob dynamics from the experimenter's field notes collected from the expert participants' "think-aloud" comments.

5.1 Machine Model Capture Accuracy

For the Haptic Camera, we can immediately observe fit performance for the one model parameter with an independent gold-standard measure, detent frequency. As seen in Table 5, the Haptic Camera detent frequency estimate was within 10 percent for the subtle-detent and moderate-detent knobs, and 26 percent for the nonsinusoidal-detent knob.

TABLE 7
Haptic Camera Accuracy Test Differences

	Position (rad)	*Velocity (rad/s)*	*Acceleration (rad/s^2)*	*Torque (mNm)*
Mean	.0012	.0016	.664	1.0
SD	.0032	.0244	.4148	1.8

* *Point-by-point differences between two trajectories measured in response to swept-sine excitation (torque or position) of knob models based on known and captured parameters for one simulated knob. Reproduced from [16].*

Fit performance across all parameters for this data set is analyzed at length in Swindells and MacLean [16]. There, the identification algorithm was run on simulated perfect and noisy data representing the typical dynamic range of real knobs. Because the model parameters were known a priori, the captured results could be compared with true model values, as kinematic and torque trajectories could be computed based on these models (results for the latter are shown in Table 7 for the simulated knob tests). This comparison demonstrated differences that are acceptably small for our purposes.

5.2 Human versus Machine Performance

Our quantitative analysis focuses on the many interesting relationships that emerged between the parameterizations found by the novice and expert participants and by the Haptic Camera. In instances of inconsistency between experts and novices, we saw the experts as more likely to achieve a given modeling objective, but we were also attentive to novice attempts and satisfaction. Additionally, because only experts performed a "think-aloud" protocol, expert comments informed a greater amount of the following discussion.

In the following, we compare human and machine identification of several specific attributes in turn.

5.2.1 Humans Confused Subtle Detents with Damping

Participants confused subtle (low-amplitude) detents with an uneven frictional effect, whereas the Haptic Camera did not. This is seen in the reversed polarity of machine and human ratings for the subtle-detent knob for parameters B_{vel} and P_{pos} in Fig. 6; humans and machine agreed that this knob had very low detent amplitude (A_{pos}). Referring to the parameter for which we have a gold-standard measure (detent frequency), we can additionally infer from Table 5 that the Haptic Camera was able to discern subtle detents from friction based on its estimate of detent frequency (3 percent relative error) which is accurate compared to the average expert participant error of 17 percent. Our concern that audio cues might give humans an advantage over the Haptic Camera in detent-frequency identification did not seem to be warranted.

5.2.2 Expert Humans Best with Unmodeled Properties

The knob with nonsinusoidal detents exhibited backlash and other nonlinearities; it was deliberately chosen to test the case of poor correspondence between the mechanical system and the Haptic Camera model. Human experts were indeed better than the Haptic Camera at matching the gold-standard detent frequency (Table 5). Novices showed less facility in doing this, but were still no worse than the Haptic Camera.

5.2.3 Humans Interpret Inertia as Friction

Novice and expert participants confused $\mathrm{B_{vel}}$ and $\mathrm{M_{acc}}$ parameters more often than $\mathrm{A_{pos}}$ and $\mathrm{P_{pos}}$ parameters (compare these parameterizations for the high-friction and high-inertia knobs in Fig. 6). For example, humans did not rate inertia very high on either the high-friction or high-inertia knob; and they rated inertia lower than friction for the high-inertia knob. It appears that, in general, they found it difficult to correctly attribute a given impedance to inertia, and had a tendency to explain it at least partially as friction. This confusion might arise from the fact that both properties (friction and inertia) have an initial resistance component as one begins to turn a knob, as hinted by both expert "think-aloud" results and experimenter observation of novices and experts. An alternative explanation is that the rendering models did not adequately convey subtle nuances of friction and inertia. In contrast to human identifications, the Haptic Camera algorithm treats position-, velocity-, and acceleration-dependent parameters as equally difficult mathematical parameters to solve, and did not incorrectly use one parameter more than others.

Participants may also have been confused by the ability to change mass with a slider. Although dynamically changing mass is a foreign concept for most physical controls, people do experience change of mass in other everyday experiences, e.g., when balancing a glass in one's hand while it is being filled up. Human's facility and error rates in dealing with this situation have been studied. For example, Turvey [17] examined the mechanisms and acuity with which participants could ascertain center-of-mass versus perceived length discontinuities when holding different baseball bats, as well as many less ordinary physical systems. He observed situations in which errors were made and held with great certainty. We hypothesize that learned behaviors from real experiences of dynamically altered mass may transfer well to active physical control use, and that this attribute is worth exploring.

5.2.4 Participant Satisfaction with Captured "Feel"

The self-reported ratings of Fig. 5 illustrate the participants' satisfaction levels after selecting slider values to match the "feel" of the five test knobs. For example, participants were significantly more satisfied with their parameterizations of the high-friction and high-inertia knobs compared to the moderate-detent and nonsinusoidal-detent knobs. Because the subtle-detent knob had small detents that were often confused with frictional texture, mean satisfaction ratings that fall between those for knobs without detents (high friction and high inertia) and knobs with detents (moderate detent and nonsinusoidal detent) are consistent with the objective data above. The lower satisfaction ratings for the moderate-detent knob and the nonsinusoidal-detent knob could be due to increased cognitive load dealing with the higher number of parameters (detents in addition to inertia and damping). Additionally, the feel of the nonsinusoidal-detent knob was impossible to match perfectly using the sliders because the rendering model being parameterized was quite different from the actual physical model. Even though participants were able to deal with some of these model differences very well (namely, detent frequency, Table 5), they may have felt more cognitive strain in the process.

5.2.5 Absolute versus Relative Estimation

Comparing expert participants and Haptic Camera values for each of the knobs and parameters in Fig. 6, one can clearly see agreement between the *relative* Haptic Camera/human values for individual parameters even when the absolute values found by each do not agree. That is, for a given parameter such as $\mathrm{M_{acc}}$ or $\mathrm{B_{vel}}$, the ratio of [experts' value for $\mathrm{Knob_n}$]/[experts' value for $\mathrm{Knob_m}$] was similar to [Haptic Camera value for $\mathrm{Knob_n}$]/[Haptic Camera value for $\mathrm{Knob_m}$]. For example, looking at the damping scores for the high-friction and high-inertia knobs, expert participants as a group did a good job estimating the relative damping levels between the different reference knobs. For the same knobs, the Haptic Camera values exhibit similar ratios to the corresponding values provided by the expert participants.

This reliance on relative processing by human participants versus absolute processing by automated capture is consistent with visual psychology research, such as Snowden [14], and is generally consistent with current psychophysics theory such as Stevens' assertion that participants make judgments on a ratio scale [15].

5.2.6 Parameter Underestimation

Fig. 6 shows that novices never picked a parameter value above 0.7, and experts only did so for two parameters. In contrast, the automated Haptic Camera identified five values above 0.7 among the 16 parameters. One could argue that the two parameters for the nonsinusoidal-detent knob are a result of unmodeleded dynamics, but the more likely reason for all five "high" values is that slight imperfections in the haptic knob renderings of high-value parameters were more perceivable to human participants than slight imperfections of low-value parameters. Assuming this reason is true, participants chose knob renderings that felt more "natural" to them, even at the expense of choosing a less accurate model parameter value. The close agreement between the automated and human identification values up to around 0.5 suggests that we observed a perceptual boundary for our haptic knob's rendering abilities—a very interesting result. For our particular apparatus, haptic designers could be relatively confident that the "feel" of parameters up to about 0.5 in Fig. 6 can be faithfully captured and rendered within good technical and perceptual tolerances.

5.3 Sticky Notes from Novice Participants

Novice sticky note analysis provides insight into the novices' ability to distinguish and understand fundamental detent, friction, and inertia renderings.

The labels summarized in Table 6 provide a strong indication that most participants were able to correctly identify the four sliders into appropriate categories—inertia, damping friction, detent amplitude, and detent frequency, respectively. For example, participant P10 used the terms "momentum" and "pudding," and P1 used the terms "weight 'whoosh'" and "friction, heavy" as labels for inertia and damping. While "whoosh" and "pudding" are not technical terms for inertia and damping, they are excellent vernacular descriptions. Although less universal and specific, P11's terms "wobbly" and "knobbly" for amplitude and frequency of detents, respectively, indicate that this individual clearly understood the concept of detents. Such terminology could greatly enhance accessibility and understanding to nontechnical users of ubiquitous computing devices containing active dynamics.

Only the labels from P9 induce serious concern that the participant did not adequately understand the effects of each slider. P9 used the same label "friction" for both the friction parameter (B_{vel}) and the inertia parameter (M_{acc}). P9 also used the same vague term "cranky" for both the detent amplitude (A_{pos}) and period (P_{pos}). P13's labels also seem a bit questionable because detent amplitude and frequency are both labeled "smoothness."

Nevertheless, at most two participants out of 15 experiencing confusion during the initial training phase of the user study is promising. More important is the suggestion that the confusion between inertia and damping (see Fig. 6) is likely due to the complexity of the particular task, rather than the participants' lack of intuitive understanding of fundamental properties of physics, because in the labelings the distinction seems clear.

5.4 Field Notes from Expert Participants

Field notes based on observation of and discussion with the expert participants are organized according to several broad themes (novice field notes were not collected, as explained earlier).

5.4.1 Strategies

Experts were fairly consistent in strategies for ascertaining parameter finding, including grasps and segmentation of the parameters. All the experts used a variety of grasps on the rendered and reference knobs to explore different dynamic properties. Initial coarse categorizations were typically performed with a whole-hand grasp, while single-finger motions (usually with the index or middle finger) were used for more sensitive, refined judgments. When comparing damping and inertia, experts typically rotated the knob slowly at first to feel some velocity-based feedback; then they made progressively faster, more jerky motions to explore inertia. Another common technique for inertia estimation was spinning the knob as fast as possible, then timing how long the knob slid past one or more fingers lightly touching the edge of the knob.

Experts typically first categorized a reference knob as being with detents or without detents. Next, they tended to refine their rendering's detents (if present), then friction, and finally inertia. That is, they used an exploration strategy of position-, then velocity-, then acceleration-based parameters. Only after this they would iterate to a final solution by tweaking whichever parameters seemed least correct, moving rapidly between reference, rendering, and sliders.

Experts also attempted to use visual cues from the spinning knob, but this strategy was (made intentionally) difficult because all knobs had uniform white plastic caps.

5.4.2 Parameter Interactions

When increasing inertia, two experts stated that this made detents feel less noticeable. One expert elaborated by saying the physical interaction between inertia and detent amplitude "felt right." In other words, based on physics, one would expect detents to be less noticeable on knobs with higher amounts of inertia. These statements suggest that the interactions between different position, velocity, and acceleration-based effects occurred as expected based on fundamental laws of physics, but these physical properties were occasionally difficult for even experts to mentally segment. One expert was frustrated by difficulties caused when damping and inertia interacted. This raises the possibility that a parameter arrangement other than that of (1) might be easier for humans (and algorithms). Parameterization approaches that could be more orthogonal in perceptual space include 1) changing the damping term to include mass (i.e., replace the current B_{vel} with B_{vel}/M_{acc}), 2) controlling the average of the bidirectional stick factors in a Karnopp model with one slider and using another slider to control their asymmetry, and 3) focusing on a hysteretic damping model.

These comments by experts also suggest that segmentation of properties independently from realistic physics could improve tool usability for designers of rendered or mechanical knobs for industrial applications. For example, designers might more easily create a physically realizable model if they could manipulate a single independent parameter remapped to a combination of physical model parameters. In other words, such an approach would distinguish as appropriate between a model manipulated directly by the designer, and a more complete but unmanageably complex model.

Physically nonrealizable models may also be interesting in their own right. For example, a momentum-like parameter that does not interact with detents or friction could theoretically be rendered on a haptic knob even though such knob dynamics would be difficult, if not impossible, to create on a mechanical knob.

5.4.3 Factors Influencing Confidence

Experts typically spent between 2 and 6 minutes adjusting the four sliders to match a single reference knob. Experts would often switch between the rendered and reference knob over a dozen times for each trial. This large amount of time and iteration per trial suggests that the task was at least moderately difficult, and suggests that even the experts required significant effort to distinguish dynamic parameters, despite their demonstrated ability to eventually achieve results that were, at minimum, consistent as a set with the reference knobs.

Whether the participants performed their somewhat challenging task with assurance must be inferred. Through observation, we noted aspects of the task that either contributed to or apparently detracted from confidence. Two observed *obstacles* were in participants' sense of control over the parameter modulation tool (the sliders) and over elements of the rendering being adjusted.

For some, the relation of slider movement to knob feel was not ideal. Although the slider action was linear in parameter value, at least one expert felt that the sliders did not act in a linear manner. This statement suggests a conflict where a linear relationship in an engineering space may not be linear in a perceptual space. Nonlinear slider mappings may be more intuitive for parameter estimation, as suggested by Stevens' power law [15].

Two experts were unsatisfied with the jittery feeling on the rendered knob (perceptual instability [2]) when all sliders were set to their maxima, either through its obscuring the actual rendering dynamics or by uncontrolled mismatch with the reference. High-inertia, high-amplitude detents are technically challenging to render [11].

In terms of confidence-*boosting* factors, we noted multiple instances of systematic, rapidly convergent identifications that presumably had a positive impact generally on those individuals' confidence. For example, one expert did not initially recognize the detents on the subtle-detent knob, but quickly discerned them by rotating the knob at different velocities. The expert then adjusted the detent amplitude (A_{pos}) and damping (B_{vel}) parameters to create an appropriate rendering of the subtle-detent knob. If this expert was not confident in perceptually relating the appropriate physics-based properties using the damping and detent sliders, he would presumably not have been able to make an appropriate rendering at all.

5.4.4 Adequacy of Rendering

Comments above on perceptual instability when model parameters were maximized relate to rendering adequacy, along with several other observations made here.

Resolution and dynamic range. One expert experienced difficulty in getting the amplitude setting of the subtle-detent knob large enough to be felt, but not too large. Conversely, two experts mentioned that the haptic rendered knob did not feel stiff enough. These dynamic range issues are common to almost all force-feedback technologies, and are gradually being addressed within the haptics community through a combination of better mechatronics and better control algorithms. For example, greater stiffness could be obtained using haptic controllers with built-in braking mechanisms [7], or carefully timed bursts of force [9].

Realness. In terms of assessing how real—as opposed to simulated—the rendered knobs felt to experts accustomed to haptic rendering, perhaps the most promising comments came from two experts who asked if the reference knobs were a combination of passive and rendered knobs. Specifically, the feel of the reference subtle-detent knob was described as "complex, sophisticated... like a haptic knob." Interestingly, two curious novice participants asked similar questions when informally chatting with the experimenter after completing their studies. This confusion between passive and rendered knobs is a strong indication that the quality, and therefore the validity, of rendered dynamic properties was reasonably good for at least some of the renderings. The experts' comments also suggest a belief that active haptic controls could potentially provide a richer dynamic feel than what is possible with most passive mechanical controls.

6 Conclusions

Subtleties in the feel of manual controls are important in accordance with the time we spend touching them; with embedded computation on the rise, this time can be expected to increase. In this paper, we have examined one metric for a tool intended to support explicit and systematic design of the *feel* of ubiquitous haptic controls. Specifically, we quantified the adequacy of an objective model identification method with respect to its capture of perceptually relevant parameters by comparing its parameterizations with those produced by humans, combined with their satisfaction with the matches that their renderings produced. We considered user study results for five mechanical reference knobs, carried out with novice and expert participants who were asked to adjust four parameters of a rendered knob to match the feel of each reference knob in succession.

We observed similar relative detent, friction, and inertia parameterizations by human expert and Haptic Camera estimation methods. Independent "gold-standard" checks of detent frequencies for the subtle-detent, moderate-detent, and nonsinusoidal-detent knobs with the Haptic Camera averaged 3.0 percent, 10.0 percent, and 26.7 percent relative accuracies, respectively, whereas human experts averaged 16.3 percent, 28.3 percent, and 7.5 percent. Our qualitative results provided additional insight on users' strategies, confidence levels, and the adequacy of our setup for the matching task; all of these factors in general tended to support the conclusions drawn from these quantitative data as well as the overall validity of the experiment.

These data suggest that expert human ability to make accurate parameterizations is more robust to irregularities such as unmodeleded nonlinearities and backlash than is an automated identification procedure. We theorize that human participants benefited in these cases from the ability to mentally parameterize the knob dynamics to a model more general than used by the Haptic Camera. Conversely, the Haptic Camera outperformed human experts and novices when an appropriate physical model was used. For most knobs, such models are relatively easy to choose and can be tested for accuracy using techniques such as confidence interval calculations on final curve fitting results (e.g., Table 4).

Our studies help to demonstrate that the Haptic Camera apparatus can effectively capture knob dynamics as perceived by a human, and give credence to its value as a tool for designing interfaces for feel.

7 Future Work

Future work should explore several key areas including technical enhancements and additional user studies.

Technical enhancements needed for the rendering setup used here include improved acceleration sensing and better inertia rendering using custom accelerometers mounted within the haptic knob cap. More intuitive algorithms (from a haptic model designer's perspective, i.e., the role played by expert users in this study) could enable designers to segment and recombine physics-based subcomponents such as inertia, friction, and detents. For example, even experts had difficulty teasing apart friction and inertia effects. Virtual mass oscillations could be reduced and more faithful detents could be achieved by developing stiffer and more stable haptic technologies.

User study enhancements would help test the relative importance of various technological enhancements. Because several participants questioned whether the five passive knobs were indeed passive, the identity of the active knobs could conceivably be hidden from the participants in matching studies where the rendered knob parameters did not change during a trial. Finally, we would like to ask humans to compare *renderings* based on human versus machine parameterizations for a more direct test of relative method adequacy.

Acknowledgments

The authors thank the National Sciences and Engineering Research Council of Canada, Precarn, and Immersion Corporation for funding support of this research. Additionally, the authors thank BMW Canada and Mazda Canada for providing physical and haptic knob samples.

References

[1] I. Brouwer, "Cost-Performance Trade-Offs in Haptic Design," MSc thesis, Dept. of Mechanical Eng., Univ. of British Columbia, 2004.
[2] S. Choi and H.Z. Tan, "Perceived Instability of Virtual Haptic Texture. I. Experimental Studies," *Presence: Teleoperators and Virtual Environments,* vol. 13, no. 4, pp. 395-415, 2004.
[3] J.E. Colgate and G. Schenkel, "Passivity of a Class of Sampled-Data Systems: Application to Haptic Interfaces," *Proc. Am. Control Conf.,* 1994.
[4] N. Cowan, "The Magical Number 4 in Short-Term Memory: A Reconsideration of Mental Storage Capacity," *Behavioral and Brain Sciences,* vol. 24, no. 1, pp. 87-114, 2001.
[5] N. Forrest, S. Baillie, and H.Z. Tan, "Haptic Stiffness Identification by Veterinarians and Novices: A Comparison," *Proc. World Haptics,* pp. 1-6, 2009.
[6] P.R. Gill, W. Murray, and M.H. Wright, *Practical Optimization,* pp. 136-137. Academic Press, 1981.
[7] Immersion Corporation, *PR-1000 Rotary Controller with Braking Actuator,* available online at: http://www.immersion.com/industrial/rotary/products, 2006.
[8] P. Jordan, *Designing Pleasurable Products: An Introduction to the New Human Factors.* CRC Press, 2000.
[9] K.J. Kuchenbecker, J. Fiene, and G. Niemeyer, "Improving Contact Realism Through Event-Based Haptic Feedback," *IEEE Trans. Visualization and Computer Graphics,* vol. 12, no. 2, pp. 219-230, Mar./Apr. 2006.
[10] W.B. Knowles and T.B. Sheridan, "The 'Feel' of Rotary Controls: Friction and Inertia," *Human Factors,* vol. 8, pp. 209-215, 1966.
[11] B.E. Miller, J.E. Colgate, and R.A. Freeman, "Guaranteed Stability of Haptic Systems with Nonlinear Virtual Environments," *IEEE Trans. Robotics and Automation,* vol. 16, no. 6, pp. 712-719, Dec. 2000.
[12] K.E. Novak, L.E. Miller, and J.C. Houk, "Kinematic Properties of Rapid Hand Movements in a Knob Turning Task," *Experimental Brain Research,* vol. 132, no. 4, pp. 419-433, 2000.
[13] C. Richard, "Friction Identification and Haptic Display of Friction," *Proc. Haptic Interfaces for Virtual Environments and Teleoperator Systems (HAPTICS),* 1999.
[14] R.J. Snowden, "Sensitivity to Relative and Absolute Motion," *Perception,* vol. 21, no. 5, pp. 563-568, 1992.
[15] S.S. Stevens, "On the Psychophysical Law," *Psychophysical Rev.,* vol. 64, no. 3, pp. 153-181, 1957.
[16] C. Swindells and K.E. MacLean, "Capturing the Dynamics of Mechanical Knobs," *Proc. Second Joint Eurohaptics Conf. and Symp. Haptic Interfaces for Virtual Environment and Teleoperator Systems,* pp. 194-199, Mar. 2007.
[17] M.T. Turvey, "Dynamic Touch," *Am. Psychologist,* vol. 51, no. 11, pp. 1134-1152, 1996.
[18] B. Woodruff and H. Helson, "Torque Sensitivity As a Function of Knob Radius and Load," *Am. J. Psychology,* vol. 80, no. 4, pp. 558-571, 1967.

Colin Swindells received the BASc degree in engineering science and the MSc degree in computing science from Simon Fraser University in 2000 and 2002, respectively. He received the PhD degree in computer science from University of British Columbia in 2007. He currently holds a Natural Sciences and Engineering Research Council of Canada Postdoctoral Fellowship (NSERC PDF) at the University of Victoria, and he is a cofounder of Locarna. He is a member of the IEEE.

Karon E. MacLean received the BSc degree in biological sciences and mechanical engineering from Stanford University in 1986, and the MSc and the PhD degrees in mechanical engineering from Massachusetts Institute of Technology in 1988 and 1996, respectively. From 1996 to 2000, she was with Interval Research Corp. She is an associate professor of computer science at the University of British Columbia, the director of Sensory Perception and Interaction Research Group (2000-present). She is an associate editor of the *IEEE Transactions on Haptics*, and the cochair of IEEE Haptics Symposium (2010-2012). She was the recipient of Peter Wall Early Career Scholar in 2001, Izzak Walton Killam Memorial Faculty Research Fellowship in 2007, and Charles A. McDowell Award in 2008. She is a senior member of the IEEE.

Kellogg S. Booth received the BS degree in mathematics from California Institute of Technology (Caltech) in 1968, and the MA and the PhD degrees in computer science from University of California, Berkeley, in 1970 and 1975, respectively. He is a professor of computer science and former director of the Media and Graphics Interdisciplinary Centre at the University of British Columbia. He has been working in the fields of computer graphics and human-computer interaction since 1968. Prior to UBC, he was a faculty member in the Department of Computer Science at the University of Waterloo (1977-1990), and before that a staff member at Lawrence Livermore National Laboratory (1968-1976).