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Reality-Based Haptic Force Models of Buttons and Switches

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***Abstract*—Accurate models of the feel of physical objects are essential to improving the realism of haptic simulations. This paper presents a method for automatically obtaining experimentally based models of general passive, nonlinear devices for use in haptic playback applications, with specific emphasis on modeling switches and buttons. The method, based on the exponentially weighted least-squares (EWLS), allows estimation of position- and direction-dependent parameters of a general nonlinear model. Results are presented for two push-button switches.**

I. Introduction

The end objective of haptic simulations is to provide a realistic and immersive virtual experience. Ideally, and with the proper technology, a user would not be able to distinguish such simulations from reality [1]. One obstacle to achieving this level of realism is the problem of modeling the feel of the environments that are to be simulated. Even with the highest quality force-feedback interface, graphics, and control software, a haptic simulation will remain deficient if the simulation does not incorporate a realistic model of how the environment should feel. One solution to this problem is to derive accurate models for haptic rendering from experimental measurements on real devices or environments [2]. Such "reality-based" modeling methods have been shown to result in haptic simulations that, when displayed to the user, more realistically replicate the feel of physical devices and phenomena [3], [4].

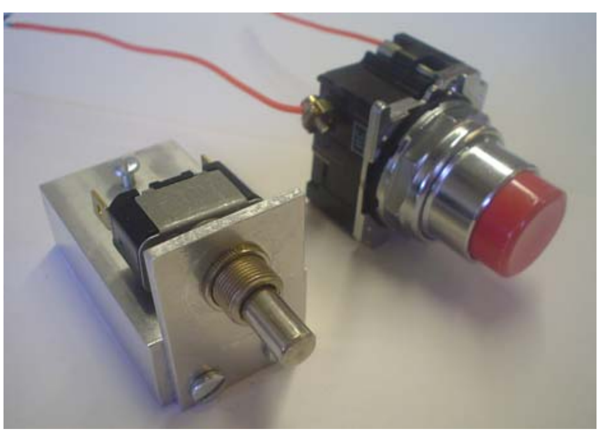

Fig. 1. Push-button switches used in modeling experiments, with PB1 on the left and PB2 on the right.

A. Objective

This paper demonstrates a reality-based approach to modeling the feel of a class of passive, mechanical devices: push-button switches. The objective is to automatically obtain nonlinear, dynamic, parameterized models for such devices from experimental force and motion profiles. These profiles are obtained by actuating the devices using an instrumented probe and recording the resulting force, position, and acceleration. Parameterized models of the target devices are then generated from the experimental data using a modified version of the exponentially weighted least-squares (EWLS) method. The models thus obtained are suitable for use in haptic simulations, and may be useful in such applications as: 1) virtual prototyping, in which realistic models of physical features of a prototype would allow a designer to evaluate a design without the need for costly physical prototypes; 2) training, in which accurate models of specific devices that the trainee must learn to use could be generated; and 3) device libraries, in which a large selection of haptic models of mechanical devices is available for use in general haptic simulations.

B. Related Work

Some other approaches to modeling buttons, switches, and knobs have been investigated. The approaches have been varied, including generating ad hoc force profiles with subjectively adjusted parameters [5]; deriving approximate models from first principles, with arbitrarily selected model parameters [6]; and recording and playing back force profiles without identifying parameterized models from the recorded data [7]-[9]. Others have generated reality-based static parameterized models of buttons and switches [4]. Initial work aimed at developing a method for identifying nonlinear dynamic models of buttons and switches is described in [10], [11]. The present work seeks to develop a general and automatic method for obtaining parameterized models of such devices.

II. Apparatus

A. Target Devices

Two push-button switches were selected as targets for the modeling method that will be described in this paper. The two buttons, designated PB1 and PB2, are shown in Fig. 1 and described in Table 1. These buttons were selected for their relatively large range of motion (13 mm and 8 mm, respectively), relatively large maximum static actuation forces (17.8 N and 11.6 N, respectively), and distinctive feel characterized by a nonlinear force/motion relationship.

B. *Modeling Testbed*

The experimental system, described in [10], consists of a direct drive linear motor to apply perturbation inputs to the target device, an internal incremental encoder for measuring the position trajectory, and an impedance head to measure the acceleration trajectory and actuation force. A detail of this system is shown in Fig. 2, in which the testbed is actuating and making measurements on button PB2. The linear motor was found to have a static open-loop force bandwidth of 118 Hz, and a closed-loop position bandwidth greater than 29 Hz. Control and data acquisition tasks were handled by a PC operating at a 4 kHz sampling rate.

III. Methods

A. *Nonlinear Model Structure*

A method for obtaining haptic models of mechanical devices must include a model structure that captures the feel of such devices. Each device may have widely varying dynamic behavior, so a modeling method that is truly general must include a model structure that is capable of describing the feel of a broad class of target devices. In the most general case, the force required to actuate a passive mechanical device is a nonlinear, time-varying function of the motion (position x, velocity v, and acceleration a) that the device is caused to undergo [10]:

$$F = f(x, v, a, t) \tag{1}$$

where F is the actuation force and t is time. The success with which (1) describes the feel of a mechanical device is strongly dependent on the structure of the model function $f(\cdot)$, with different target devices generally requiring different structures to accurately model their dynamic behavior. This, of course, requires customized modeling that limits the generality of a given modeling scheme.

One candidate structure that is well suited to approximating the feel of a wider class of mechanical devices is derived by generating a multivariable Taylor series expansion of (1) about an arbitrarily varying operating

TABLE 1
Target Devices for Modeling Experiments

	Push-Button #1	Push-Button #2
Designation	PB1	PB2
Description	Eaton 0150 normally open	Cutler-Hammer 1090 normally closed
Stroke (mm)	13	8
Maximum Static Force (N)	17.8	11.6

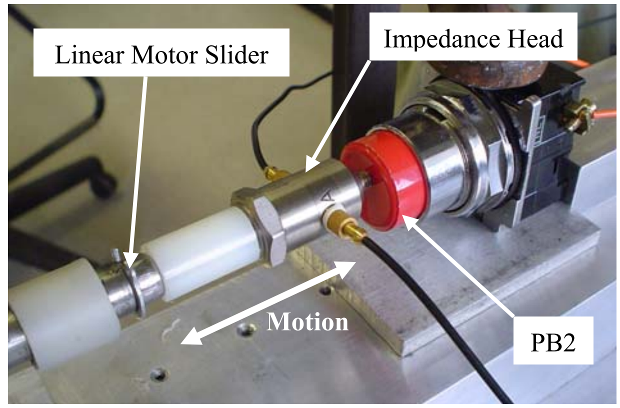

Fig. 2. Detail of testbed system making measurements on PB2. Not shown: encoder, motor drivers, control system.

point [11]:

$$F = \begin{cases} m^+(x)a + b^+(x)v + k^+(x)x + F_o^+(x), & v > 0 \\ m^-(x)a + b^-(x)v + k^-(x)x + F_o^-(x), & v < 0 \end{cases} \tag{2}$$

where m, b, and k are freely varying mass, damping, and stiffness parameters that are functions of the direction of motion (as indicated by the superscripts $^+$ and $^-$), and the position x at which the model is evaluated. The F_o term represents a varying offset force that is a product of the Taylor series expansion, but corresponds physically to a combination of a spring offset and dry friction forces. The structure given by (2) has been shown to accurately model a one degree-of-freedom system specially designed with inherent nonlinearities and known physical parameters [11]. The present work seeks to apply (2) to the more general problem of modeling existing mechanical devices, with particular emphasis on modeling buttons and switches for use in haptic simulations.

B. *Input Design*

Selection of a single, general-purpose perturbation input to excite the dynamics of a wide class of nonlinear devices is problematic; the nature of nonlinear systems prohibits *a priori* selection of optimal input frequency ranges and waveforms for estimating the parameters of nonlinear models. Selection of inputs is therefore generally based on intuition and experience, with an underlying objective of maximizing the power level present in the signal over a large range of frequencies, resulting in model parameters that are valid for a wide range of operating conditions. The approach taken in the present work was to select bidirectional position perturbation inputs that 1) contain a frequency range that is as large as possible, while remaining within the bandwidth of the perturbation system and safety limits of the target devices, and 2) span the entire travel of the target device. Various inputs were evaluated, including single frequency sinusoids, swept sine waves, pseudo-random binary sequences (PRBS), and small-amplitude swept sines or PRBS signals on large amplitude sinusoids.

C. Exponentially Weighted Least-Squares

The system identification technique selected for a given modeling application is dictated primarily by the model structure. An estimation method, based on exponentially weighted least-squares (EWLS), has been developed for estimating the position- and direction-varying parameters of model (2). The EWLS algorithm is a recursive method for estimating time-varying parameters of linear models [12], with current data points being weighted more heavily than past data points. The amount of relative weighting is determined by the following cost function J, in which the residuals, e_i, through the current (k^{th}) instant are multiplied by a sample-specific exponential weighting term:

$$J_k = \sum_{i=1}^{k} \beta_i e_i^2 = \sum_{i=1}^{k} \lambda^{k-i} e_i^2 \tag{3}$$

In this equation, $\beta_i = \lambda^{k-i}$ is the weighting applied to the i^{th} residual and λ, called the "forgetting factor," is a dimensionless constant between 0 and 1 that determines the rate at which past data points are forgotten in the current time (k^{th}) estimate of the model parameters. Larger values of λ result in heavier weighting of past data points. The equations of the EWLS algorithm can be found in [12].

D. Modeling Algorithm

1) Data Collection and Preparation

The first step in the modeling process is to actuate the target device and record the bidirectional position, acceleration, and force data resulting from the input motion trajectory. In preparation to apply the EWLS algorithm, it is necessary to pre-process the experimental data to adapt the linear, time-varying parameter estimation algorithm to the problem of identifying nonlinear (position- and direction-dependent), time-invariant models. This is accomplished in the following steps:

a. Directional Grouping: The entire data set (position, velocity, acceleration, and force) is grouped according to direction of travel, based on examination of the velocity trajectory, which is estimated from the measured position. In this paper positive and negative direction data are indicated by the superscripts "+" and "-", respectively.

b. Sorting by Position: Each data set is sorted by position, ordered from low to high values of x.

The above operations result in two data sets, one containing data recorded during travel in the positive direction, one containing negative direction data, and each ordered according to position. Each set contains m measurements of the position, velocity, acceleration, and force ($x(k)$, $v(k)$, $a(k)$, and $F(k)$ where $k = 1 \ldots m$), with each measurement corresponding to an x-location, rather than an instant in time. It follows that data in the vicinity of the k^{th} data point are spatial, rather than temporal, neighbors; data point k+1 and k-1 may have been sampled at widely different times, but, due to their spatial proximity, lie adjacent to data point k after undergoing the grouping/sorting operations described above. It also follows that consecutive data points may have widely differing velocity, acceleration, and force, despite their closeness in position. This is again a result of the grouping/sorting operations; data collected during different passes of the actuated probe may have different characteristics due to the varying input. The result is a rich input, with parameter estimates in each spatial region derived from data points with similar spatial locations, but with a wide range of velocities and accelerations.

2) Parameter Estimation

With the data grouped and sorted, they are in the proper form to be used as inputs to the EWLS estimation algorithm. The position-varying parameters in (2) are estimated for each direction by sequentially stepping through the data points in each directional set, and estimating a set of model parameters at each point using the EWLS method. The result is two tables of model parameters, one containing positive-direction model parameters as a function of the position x, and the other containing parameters for the negative-direction data.

3) Post-Processing

The modified EWLS method yields thousands of model data points distributed unevenly over the x-range of the model space. Some of these data points occur at the same x-values, due to the multiple passes of the instrumented probe during data collection. At such points, each model parameter is replaced by the mean of all instances of that model parameter that occur at the same x-value. The result is a set of unevenly spaced data points, with unique model parameters at each x-value. To reduce the size of the data set, the data are resampled at a spacing of Δx (called the resampling increment) and interpolated in cases when there is not a data point corresponding to a specified x-value. The post-processing operations, applied to fictitious positive-direction stiffness data, are illustrated in Fig. 3. In the figure, unevenly spaced data, with repeated stiffness values at certain values of x, are averaged, resampled and interpolated to produce evenly spaced data with no repeated points.

The reality-based models obtained in these steps are well suited for playback in haptic simulations. The models are in the form of look-up tables, with model parameters m, b, k, and F_o tabulated as functions of x. For each device there are two tables, one for each direction.

IV. Results

The methods described in previous sections were applied to modeling the two push-button switches, PB1 and PB2.

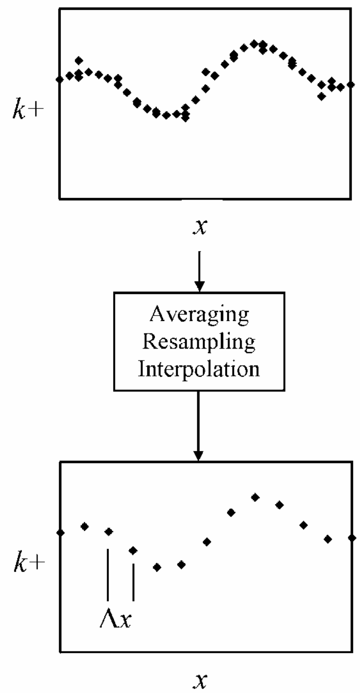

Fig. 3. Post-processing of unevenly-spaced, repeated model parameters

The results of these experiments will now be presented.

A. Push-Button #1 (PB1)

Seven candidate perturbation inputs were applied to PB1, with the best input being selected as the one that resulted in the set of model parameters with the highest variance-accounted-for (VAF). The VAF represents the proportion of the variance of the force that is predicted by the model, and is equivalent to the coefficient of determination used in linear regression applications [13]. The input that resulted in the highest VAF for PB1 was a single frequency (2 Hz) sinusoid with an amplitude of 5.59 mm. For this input, models were generated using various values of forgetting factor (λ = 0.9990…0.9999) and resampling increment (Δx = 0.05…4 mm). The VAF was calculated for each combination of λ and Δx, the results of which are shown in Fig. 4. It is clear from this figure that the quality of the parameter estimates, as measured by the VAF, is a function of both the forgetting factor and the resampling increment. The optimal combination, based on the highest VAF, was

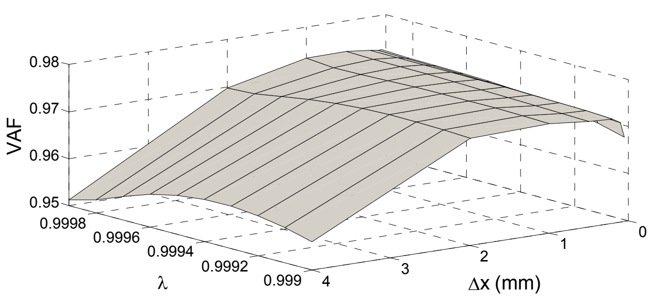

Fig. 4. Variance-accounted-for (VAF) as a function of forgetting factor (λ) and resampling increment (Δx) for PB1

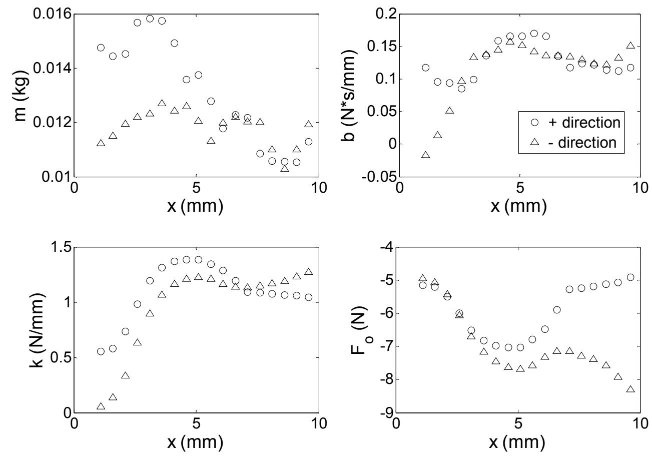

Fig. 5. Direction- and position-dependent model parameters for PB1

found to be λ = 0.9999 and Δx = 0.5 mm. The estimated model parameters for this combination are shown in Fig. 5. In this figure, the position- and direction-dependence of the model parameters is apparent.

To test the ability of the resulting models to describe the dynamic forces necessary to actuate PB1, a 1.5 Hz sinusoidal validation input was applied to the device, and the resulting forces were recorded. The forces predicted by the reality-based model were compared to the measured forces, as shown in Fig. 6, which verifies the quality of the experimental model. The effect of varying the forgetting factor on the nature of the parameter estimates is illustrated in Fig. 7 for the positive-direction only. Note that increasing the forgetting factor results in a smoother parameter profile, which is most apparent in the trace of the offset force (lower right corner). This trend is due to the fact that higher values of λ result in heavier weighting of more distant data points in the parameter estimates, resulting in a smoothing effect.

To investigate the ability of the model structure and estimation method to realistically capture the feel of PB1, the frequency content of the predicted and measured forces were also compared, as shown in Fig. 8, which shows the Fast Fourier Transform (FFT) of each trace. Note that the model accurately represents the frequency characteristics of

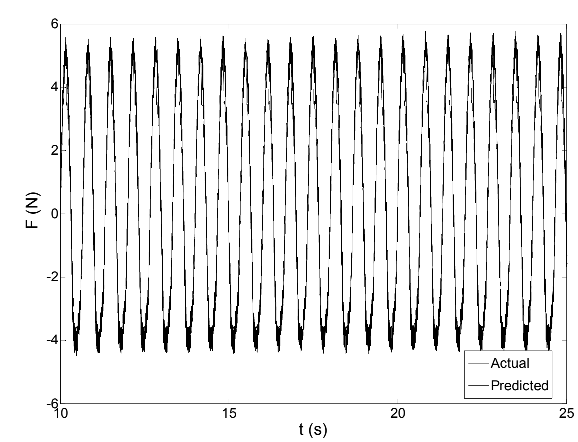

Fig. 6. Measured and predicted forces based on the model of PB1

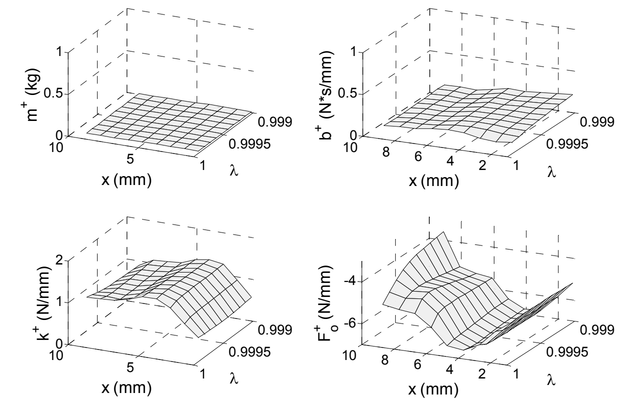

Fig. 7. Positive-direction model parameters as a function of forgetting factor (λ) for PB1

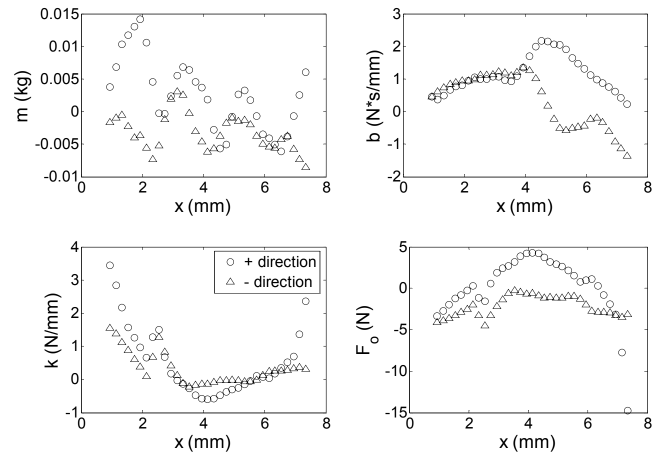

Fig. 9. Direction- and position-dependent model parameters for PB2

the target device.

B. *Push-Button #2 (PB2)*

Eight candidate inputs were applied to PB2. The results presented here are for a 1-5 Hz swept sine, of amplitude 1 mm, superimposed on a 0.5 Hz, 2.9 mm sine. The optimal model parameters were found to result from a combination of λ = 0.9998 and Δx = 0.2 mm. The resulting model parameters are shown in Fig. 9, and the measured and predicted forces in Fig. 10. The FFT of the measured and predicted forces are shown in Fig. 11. The effect on parameter estimates of varying the forgetting factor is illustrated in Fig. 12.

V. Discussion

The results of this research suggest that the nonlinear model structure and identification method presented in this paper are capable of modeling the feel of passive buttons and switches. It has been shown that the quality of the haptic model is a function of the forgetting factor and resampling increment, with a drastic drop-off in model quality for resampling increments larger than 2 mm (see Fig. 4). It is probable that the value at which such a drop-off occurs depends on the scale of model features for a particular target device; for devices with quickly varying dynamics, it is clear that more closely spaced model parameters would be necessary to describe the dynamics. The relationship between the forgetting factor and model quality may also be related to the spatial rate of variation of a device's dynamics, with quickly varying devices requiring a lower value of forgetting factor in order to accurately track the model parameters. Higher values of λ resulted in models whose parameters vary more smoothly with position. Although the values of λ appear high when taken in the context of traditional application of the EWLS algorithm, the present application causes many more data points to be present in a given spatial range, due to repeated traversals of the target device's range. The result is that high values of the forgetting factor are necessary to incorporate small spatial ranges of data into the parameter estimate at a given point.

During the process of refining the methods described here, variations on the model (2) were evaluated. These variations included eliminating the offset force term and removing the direction-dependence in the model. Both modifications were found to adversely affect the quality of the resulting models, as determined by visual inspection of

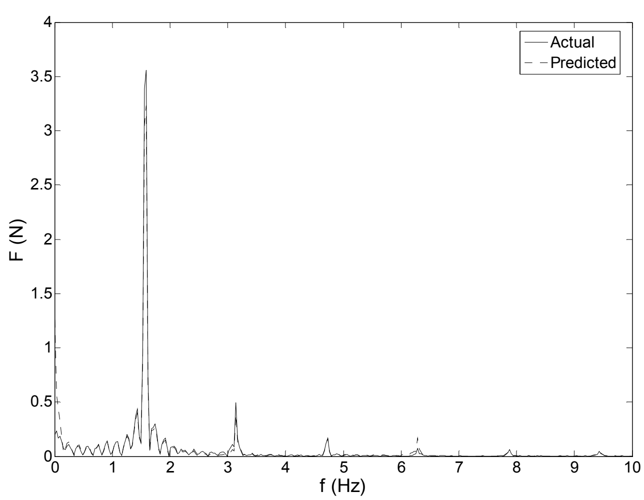

Fig. 8. Measured and predicted FFT of forces based on the model of PB1

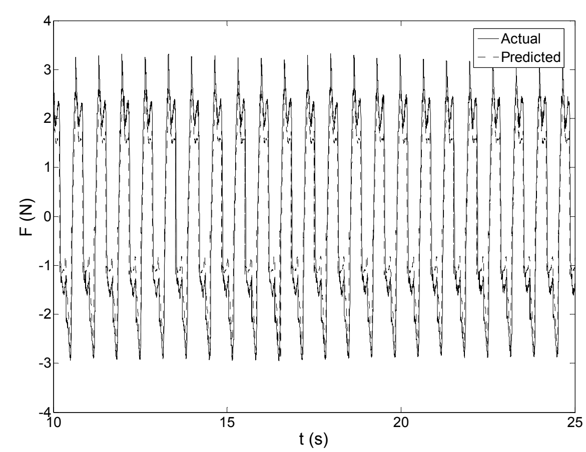

Fig. 10. Measured and predicted forces based on the model of PB2

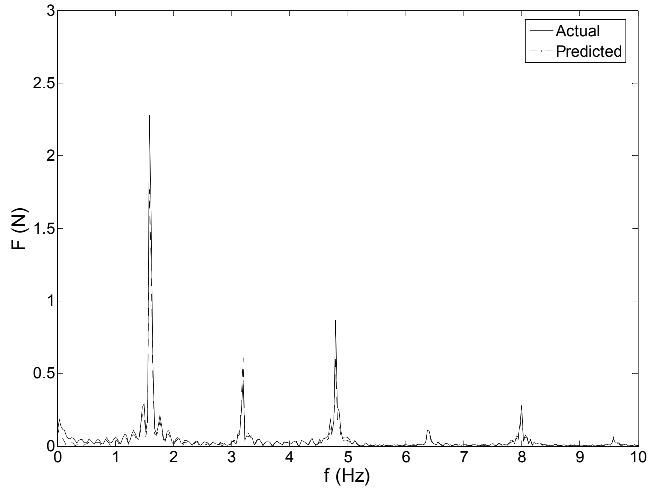

Fig. 11. Measured and predicted FFT of forces based on the model of PB2

the resulting force profiles and through quantitative comparisons of the VAF. Future model improvements may include addition of stiction-type friction terms or velocity dependence of model parameters.

A limitation of the present method is that it always estimates a complete model, regardless of whether a complete model is necessary to accurately represent the feel of the target device. There may be certain devices whose behavior is strongly dominated by a subset of the terms present in (2). For example, the behavior of certain devices may be dominated by the stiffness term, making the effects of damping or inertia negligible by comparison. In such cases it would be desirable to neglect the terms that contribute little to the total force, resulting in a simpler model with fewer terms to pass through noise effects.

The quality of the models generated in this work was determined strictly from objective, engineering analyses of the time- and frequency-domain characteristics of the forces predicted by the models. Work is under way to evaluate these reality-based methods by displaying the resulting models to users using a simple haptic interface, and asking the users to subjectively rate the quality of the models. These methods are also being applied to more challenging target devices, including turn-signal switches with highly nonlinear dynamics. Although these methods have been applied specifically to modeling buttons and switches, they should be equally applicable to other passive, nonlinear, mechanical devices.

ACKNOWLEDGMENT

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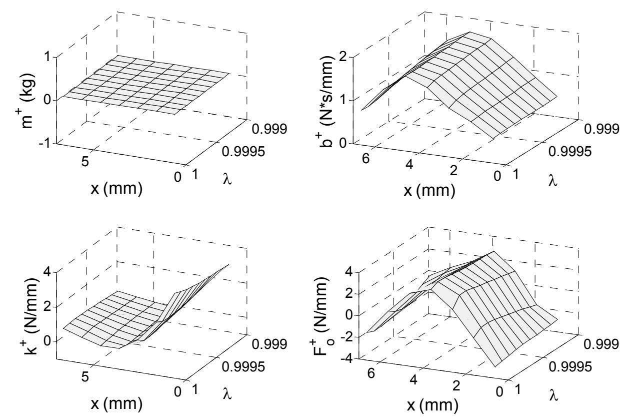

Fig. 12. Positive-direction model parameters as a function of forgetting factor (λ) for PB2

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