Identification of Nonlinear Passive Devices for Haptic Simulations

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Abstract

This paper describes a method for identifying models of a class of nonlinear passive devices, such as switches, knobs, and buttons. A general nonlinear impedance model is presented, which accounts for dynamics that change with both position and direction. Exponentially-weighted least-squares is used to fit the nonlinear model to experimental data from a specially designed physical 1-DOF test device with inherent nonlinearities. The data are obtained using an instrumented linear probe.

1. Introduction

An important aspect of improving the realism of haptic simulations is that of accurately modeling the feel of complex devices. One area of particular interest is modeling the forces felt as a user interacts with passive devices, such as switches, knobs, levers, and other controls or tools. Consider, for example, an automobile turn signal switch. As a user actuates the switch, a rather complex force profile is felt, due to the nonlinear nature of the switch. Detents, friction, backlash, and other discontinuities contribute to the distinctive "feel" of a turn signal switch. Additionally, a description of the force profile may vary with position, direction, or other parameters. Creating a model of such a device for use in haptic simulations (in which a user actuates a virtual turn signal switch and feels the resulting force profile) is a challenging proposition. The objective of the work presented in this paper is to create the tools needed to effectively model complex, nonlinear devices.

1.1. Related work

There are many approaches to modeling the feel of complex devices. A common approach is to examine the design of a device and formulate idealized equations, based on engineering assumptions, to describe the force profile. The parameters of these idealized models are often selected arbitrarily and then subjectively adjusted until the virtual device feels like the real object [1]. Examples of this approach include the work done by Allotta et al., in which a haptic simulation of a cam-based rotary knob was created, the model for which was derived from first principles using arbitrarily assigned parameters [6]. Hayward and Armstrong [5] took this approach in applying various friction models to haptic rendering. The models were simulated using a planar haptic device, but no mention was made of how the model parameters were obtained. There are many other examples in the literature of using idealized engineering models to describe the feel of passive devices.

Although this approach has theoretical appeal, in actuality its success is limited by the complexity of the device to be modeled (the "target device") and the modeler's knowledge of the model parameters, which may be highly dependent on material properties, lubrication, assembly method, tolerances, and an infinite variety of other factors. Clearly, there is a need for an experimental approach to generating models for complex, nonlinear devices [2]. These "reality-based" models are derived from measurements on physical target devices, and may be used to enhance haptic simulations by providing a more realistic force display for complex virtual devices.

There are two approaches to reality-based modeling of interaction forces that are most relevant to the work presented in this paper. The first is to actuate a physical device using an instrumented probe, record the resulting interaction forces, and then play the force profile back, *as is*, in haptic simulations. In this approach, a model is not fitted to the recorded force profile. It is generally assumed that the force felt by the user is a function of position only, and not dependent on other parameters (such as velocity or acceleration). An example of this is given by Angerilli et al. [7], in which the force-position relationship of an automotive gearshift was recorded and played back on a specialized haptic interface. A parameterized model

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of the force-position relationship was not obtained. Weir et al. [8] used an instrumented probe to record force profiles for three push button switches. The forces were plotted vs. position, velocity, and acceleration, giving a rather complete description of the feel of each switch. The data accounted for the dependence of the force on velocity and acceleration, but a parameterized model was not identified.

The advantage of the recording/playback approach is that it is easily implemented, and does not require system identification methods to model the force profile. The disadvantage is that the method does not account for the dynamics of the target system. It is, in essence, a static description of the stiffness of the target device, and makes no allowance for forces dependent on velocity or acceleration. It is also difficult to adjust the feel of a virtual device without making a new measurement on a different device. For example, if it is desired to change the feeling of mass or friction of a virtual device, the recording/playback approach has no way to account for the changed mass or friction, because the force profile is strictly a force recording, with no description of the causes of those forces.

The second approach is to actuate a physical device using an instrumented probe, record the resulting forces, and then fit a parameterized model to the recorded data. The model may be a function of position only, or a more complicated function of position and other variables (such as velocity and acceleration). The advantage of this method is that it has the ability to describe the dynamics of a target device, and so the force output may change depending on how the user actuates the device (e.g., the force may depend on velocity, as with a dashpot, or on acceleration, as with a mass). This approach therefore allows a more complete description of a target device. It is also more versatile, allowing the user to adjust the feel of the virtual device by changing the model parameters. For example, if it is desired to change the feeling of friction, it is a simple matter to change the magnitude of the friction parameter in the model.

There are multiple examples of using reality-based measurements to generate parameterized models. Dupont et al. [1] successfully estimated the mass and coefficient of friction of blocks during a teleoperated stacking task using static measurements of contact force. Richard et al. [4] discusses reality-based estimation of the parameters of a modified Karnopp's friction model applied to a block sliding on various surfaces; an active probe was used to actuate the block, and the estimates were obtained using ordinary least-squares. Okamura et al. [15] and Okamura et al. [16] addressed the problem of modeling vibration for haptic simulations. An instrumented stylus was used to acquire vibration data during tapping, stroking, and puncturing tasks. A parameterized model was fitted to the measured data for each task.

MacLean and Durfee [9] and MacLean [10] proposed a reality-based approach to estimating models of switches. An active probe was used to apply position inputs to a toggle switch and record the resulting force. This data was used to generate a segmented impedance model of the switch. A different, specialized input was used to estimate each of the model parameters. The parameters were estimated individually, with the mass estimate dependent on the estimate of the damping, which was dependent on the estimate of the stiffness. Problems associated with this approach limited the ability to estimate higher-order parameters; only an estimate of the stiffness was obtained. Colton and Hollerbach [11] used an instrumented probe to actuate a nonlinear test system, and fitted a segmented impedance model to the experimental data. Parameters estimates were obtained simultaneously using ordinary least-squares. The stiffness and mass were estimated accurately, but, due to noise and other factors, only a poor estimate of damping was obtained.

1.2. Approach

The objective of the present research is to develop the methods and apparatus for obtaining parameterized models to describe the feel (relationship between position, velocity, acceleration, and force) of 1-DOF nonlinear passive devices. The approach is to use exponentially-weighted least-squares (EWLS), a recursive algorithm that estimates the parameters of a general nonlinear model from data obtained from measurements on physical devices.

2. Model structure

2.1. General nonlinear model

General mechanical devices may exhibit a nonlinear, time-dependent relationship between force and position, velocity, and acceleration:

$$F = f(x, v, a, t, \boldsymbol{\theta}) \qquad (1)$$

where F is the force, x position, v velocity, a acceleration, t time, and $\boldsymbol{\theta}$ a vector of parameters of the model (1). If a user causes a device to undergo motion described by x, v, and a, then the device will exert a force F on the user. Thus, the motion variables are

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considered the inputs to the system and the force the output, as implied by (1). This approach is typical in haptic simulations, in which a user interacts with a virtual environment by manually controlling the position and/or orientation of a haptic interface.

The aim of the present research is to automatically estimate models of nonlinear devices for use in haptic simulations. This objective reduces to the system identification problem of determining a suitable model function f in (1), and estimating its parameters $\boldsymbol{\theta}$ from experimental measurements of the output F and the inputs x, v, and a. One of the difficulties associated with this problem is that current methods for estimating the parameters for nonlinear models require that the specific form of the nonlinear model (1) be known *a priori* [3]. So, for a system identification method to successfully model a device, the internal structure of the device must be known in advance.

2.2. Locally linear model

A general approach to modeling nonlinear devices is to work with a linear approximation of the true behavior. If the target device's dynamics are assumed time-invariant, then (1) may be approximated by a multivariable Taylor series expansion about the base point $\{x_o, v_o, a_o\}$, truncated after the first-order terms:

$$F = f(x,v,a,) \approx f(x_o,v_o,a_o) + (x - x_o)\frac{\partial f}{\partial x} + + (v - v_o)\frac{\partial f}{\partial v} + (a - a_o)\frac{\partial f}{\partial a} \quad (2)$$

where the partial derivatives are evaluated at the base point. Defining the constants

$$F_c \equiv f(x_o,v_o,a_o),\ k \equiv \frac{\partial f}{\partial x},\ b \equiv \frac{\partial f}{\partial v},\ m \equiv \frac{\partial f}{\partial a} \quad (3)$$

and substituting them into (2), results in:

$$F = m(a - a_o) + b(v - v_o) + k(x - x_o) + F_c \quad (4)$$

Returning to the assumption of time-invariance, it is noted that x_o will not change with time, requiring that v_o and a_o be zero. Making the necessary changes to (4) and reordering its terms results in:

$$F = ma + bv + kx + F_c - kx_o \quad (5)$$

The parameters F_c and x_o are not separately identifiable by current estimation schemes, and so are combined:

$$F_o \equiv F_c - kx_o \quad (6)$$

Substitution into (5) results in:

$$F = ma + bv + kx + F_o \quad (7)$$

Thus, a general model of the form given by (1), in which the output force is a nonlinear function of the motion variables, may be approximated at each value of x by a linear mass-spring-damper model (7). The final term represents an offset force due to the Coulomb-like friction plus an offset in the spring. A final modification to the model is obtained by allowing the parameters to vary continuously with position and direction of motion over the range of the target device:

$$F = \begin{cases} m^+(x)a + b^+(x)v + k^+(x)x + F_o^+(x), & v > 0 \\ m^-(x)a + b^-(x)v + k^-(x)x + F_o^-(x), & v < 0 \end{cases} \quad (8)$$

where the superscripts ($^+$ and $^-$) indicate the direction of motion for which the model parameters are valid. The direction- and position-dependence provide the flexibility needed to model a wide variety of devices.

The model described by (8) is appropriate for several reasons. First, the derivation of the linearized model is founded on the Taylor series expansion, and so represents a true linear approximation to the dynamics at a given operating point. As long as the excursion from the operating point is small, the linear approximation will be valid. This should always be the case, since (8) is based on varying the operating point so that it matches the position at which the function is evaluated. Second, many mechanical devices are actually comprised of mass, damping, stiffness, and friction elements, and so may be represented accurately by a model of this form. Third, existing identification methods may be modified to estimate the parameters appearing in (8). Lastly, most people have an intuitive feel for the types of forces present in (8). In haptic simulations, in which the objective is for a device to feel realistic, there are obvious benefits of using models with intuitive appeal.

3. Procedure

The problem at hand is to fit a model of the form given by (8) to data obtained from measurements on a physical target system. This is equivalent to estimating the position- and direction-varying parameters in (8). The procedure for formulating these parameter

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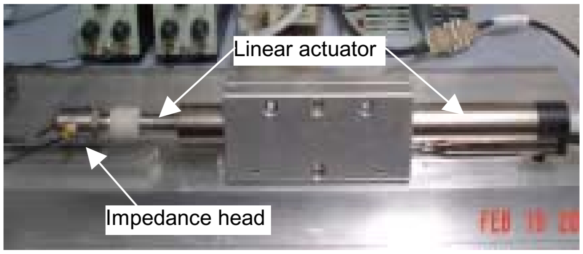

Fig. 1. Modeling testbed actuator and impedance head

estimates is comprised of three steps: data acquisition, data preparation, and parameter estimation.

3.1. Data acquisition

The actuation system must be capable of actuating the target device and recording the resulting force, position, velocity, and acceleration. A probe with these capabilities has been constructed, comprised of a direct-drive linear motor with an internal linear encoder, and an impedance head capable of measuring force and acceleration. Velocity is estimated by differentiating the position signal. A portion of the system is shown in Fig. 1, and details are given in [11].

The quality of the parameter estimates is a function of the input used to actuate the target system. Specifically, the frequency content of the input signal must span the range of frequencies corresponding to the individual model parameters [14]. This implies the need for an input signal containing multiple discrete frequencies, or a continuous range of frequencies. An additional requirement is imposed by the assumption that the model parameters vary with position: the input signal must also cause the actuator to travel through the entire x-range of the target device, thereby allowing estimation of the parameters at each value of x. An input that meets these requirements is a constant amplitude swept-sine. The amplitude is selected to span the entire range of x-values, and the frequency sweep is selected to span the anticipated range of frequencies of the target device. Data are acquired as the probe moves through the swept-sine trajectory.

3.2. Data preparation

The instrumented probe follows the position trajectory over time, and so the data (x, v, a, and F) obtained are tabulated vs. time. The parameters in the proposed model (8), on the other hand, are assumed to depend on position and direction of travel. The time-varying data, therefore, must be re-cast into a position- and direction-varying form. This is accomplished by first grouping the data according to direction of travel, as determined by the sign of the filtered velocity. Each data group is then sorted by position.

3.3. Parameter estimation

The estimation method selected for the present work is exponentially-weighted least-squares (EWLS), a recursive algorithm for estimating model parameters from experimental data. Although generally applied to time-varying models, EWLS is suitable for position-varying models, after sorting and grouping the data.

Starting with an initial estimate of the parameters, EWLS steps through each data point (in this case, the measured data at each position), recursively estimating the model parameters as a function of position. EWLS is capable of estimating nonlinear model parameters by weighting current data more heavily than previous samples. The relative weighting of current vs. past data is determined by selecting the “forgetting factor” λ, with $0 < \lambda \leq 1$. Large values of λ result in greater emphasis on past data, with $\lambda = 1$ corresponding to the standard recursive least-squares, in which all samples contribute equally to the recursive estimate. Smaller values of λ allow more accurate tracking of varying parameters by weighting more heavily the recent data.

Table 1. EWLS equations

$\mathbf{L}(i+1) = \dfrac{\mathbf{P}(i)\boldsymbol{\varphi}(i+1)}{\lambda + \boldsymbol{\varphi}^T(i+1)\mathbf{P}(i)\boldsymbol{\varphi}(i+1)}$	(a)
$\mathbf{P}(i+1) = \dfrac{1}{\lambda}\left[\mathbf{P}(i) - \mathbf{L}(i+1)\boldsymbol{\varphi}^T(i+1)\mathbf{P}(i)\right]$	(b)
$e(i) = y(i+1) - \boldsymbol{\varphi}^T(i+1)\hat{\boldsymbol{\theta}}(i)$	(c)
$\hat{\boldsymbol{\theta}}(i+1) = \hat{\boldsymbol{\theta}}(i) + \mathbf{L}(i+1)e(i)$	(d)

The EWLS algorithm is summarized in Table 1, in which $\boldsymbol{\varphi}(i)$ is a row vector of input data at the current (i^{th}) position step, $y(i)$ is the output, $e(i)$ is the prediction error, $\hat{\boldsymbol{\theta}}(i)$ is a column vector of parameter estimates, and $\mathbf{L}(i)$ and $\mathbf{P}(i)$ are intermediate matrices used in computing the estimate [14]. In the case of the model (8), these variables are defined as follows:

$$\boldsymbol{\varphi}(i) = \begin{bmatrix} a(i) & v(i) & x(i) & 1 \end{bmatrix} \tag{9}$$

$$y(i) = F(i) \tag{10}$$

$$\hat{\boldsymbol{\theta}}(i) = \begin{bmatrix} \hat{m}(i) & \hat{b}(i) & \hat{k}(i) & \hat{F}_o(i) \end{bmatrix}^T \tag{11}$$

4. Target device

These methods have been applied successfully to a target device comprised of elements with known model parameters. The target device (see Fig. 2) consists of nonlinear (hardening) springs, a mass, and a dashpot. The springs were designed to exhibit constant stiffness over certain ranges of x, and rapidly changing stiffness over other ranges. This was verified in an independent experiment using an Instron load frame. The x-varying stiffness thus obtained is shown in as a solid line in the upper plot of Fig. 3.

5. Experimental results

In the initial experiments, the instrumented probe actuated the target device with a 90 second, 1-4 Hz swept-sine position input over a 50 mm range, sampled at 4 kHz. A dashpot was not included in this experiment. After grouping the data by direction and sorting by position, the EWLS algorithm was used to estimate the model parameters as a function of position. A forgetting factor of $\lambda = 0.999$ was found to give satisfactory parameter tracking for this target device. The parameters were interpolated at 1 mm increments. The results for both directions are shown in Fig. 3. Note that the stiffness estimate closely matches the actual stiffness (determined using the load frame). The damping is estimated to be zero, as expected without the dashpot in place. The mass estimate tracks, with some variation, the actual constant mass of the system. The offset force tracks reasonably well that portion that is due to the spring offset, as determined using the Instron load frame. Any discrepancy in the offset force may be due to the friction, as shown in equation (6).

A 2 Hz sinusoidal input was applied to the system in order to verify the estimated model's ability to predict the output force of the target device. The result is shown in Fig. 4, in which it is clear that the model closely predicts the output of the physical system.

6. Discussion and conclusion

The preliminary results presented in this paper indicate that the EWLS method is capable of estimating the position- and direction-varying parameters of a model of the form described by (8). The parameters are estimated simultaneously, which is an improvement over certain other methods that estimate parameters individually, with the quality of each parameter estimate depending on the estimate of the other, previously estimated parameters. It has also been shown that the EWLS method, when used in

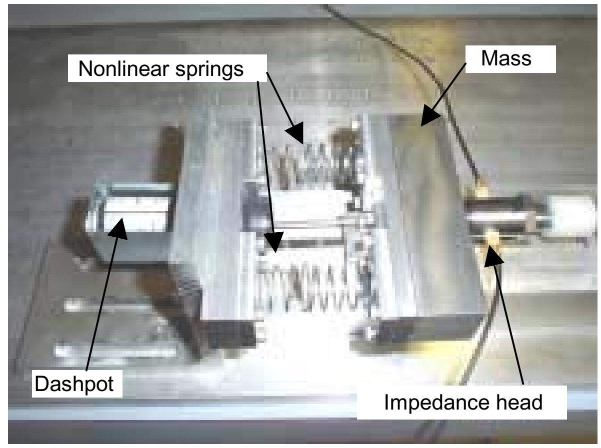

Fig. 2. Nonlinear test system

conjunction with a swept-sine input, is capable of accurately estimating the mass of a target device, which is often the most difficult parameter to estimate.

Current research is aimed at applying these methods to more complex nonlinear systems, such as an automobile turn signal lever. Initial results suggest that the present methods will be able to identify models of these types of devices. These models will then be used in haptic simulations. Other approaches are being investigated, including fitting segmented models to the experimental data, which has the appeal of reducing the overall complexity of the parameter variations. Take, for example, the model parameters shown in Fig. 3. The stiffness parameter, k, and the offset force, F_o, are approximately constant over the range $0 \leq x \leq 12$ mm. It would therefore simplify the model structure by making that position range a single segment, with the stiffness and offset force constant values in that range.

7. Acknowledgments

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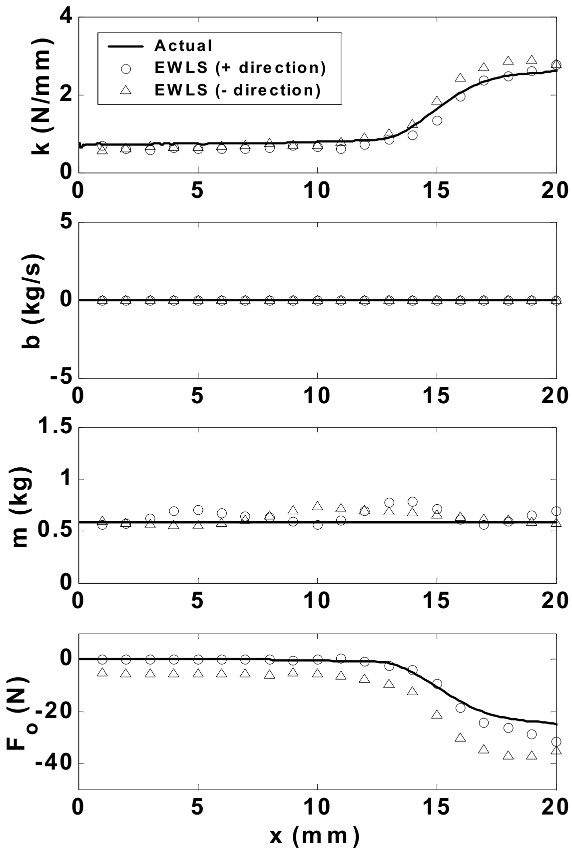

Fig. 3. Model parameters estimated using EWLS and interpolated at 1 mm intervals

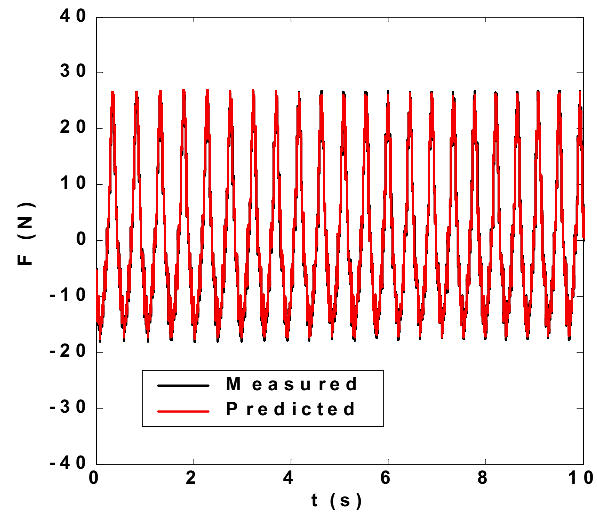

Fig. 4. Forces, measured and predicted

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