A Method for Dynamics Identification for Haptic Display of the Operating Feel in Virtual Environments

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***Abstract*—Realistic dynamics models are important for haptic display for virtual reality systems. Such dynamic models are desirably obtained via experimental identification. However, traditional dynamics identification methods normally require large sized training data sets, which maybe difficult to meet in many practical applications. To obtain the dynamics models, we present, in this paper, an identification method using support vector machines regression algorithm which is more effective than traditional methods for sparse training data. This method can be used as a generic learning machine or as a special learning technique that can make full use of the available knowledge about the dynamics structure. The experimental results show the application of our method for identifying friction models for haptic display.**

***Index Terms*—Dynamics identification, haptic display, support vector machines (SVM), virtual-reality (VR)-based training.**

I. Introduction

HAPTIC display is an effective interaction aid in improving the realism of virtual worlds [1]. The ability to touch, feel, and manipulate objects in virtual environments can provide much greater immersion than before [2]–[4]. However, successful implementation of haptic display in practical applications desires dynamics models to be incorporated [5]. Among the dynamic effects to be modeled, friction is a factor important to many applications such as virtual-reality (VR)-based surgical training [6], [7]. Friction modeling has been extensively explored in robotics community [8]. The modified Karnopp friction model proposed by Cutkosky *et al.* [9] introduced stick–slip and viscous friction effect. The LuGre model [10] can capture the experimentally observed static and dynamic characteristics of friction. The cost paid for the dynamics characteristic prediction of this model is the dependency of the friction on an immeasurable internal state. Neural-network-based learning has also been studied for friction modeling [11]. The limitation with this method lies in the overfitting problem when the training data are sparse. In general, a problem with the traditional least square and neural-network-based identification method is that they are based on empirical risk minimization principle, so that they need a large number of training data sets and they tend to be sensitive to unknown error distribution models.

Recently, the support vector machine (SVM) [12] has been explored for data classification and regression. Based on structure risk minimization (SRM), SVM serves as a favorable tool for reconstructing the approximation of a function from sparse training data. The interesting feature of the SVM-based method is that the resulting model is only recorded by the information of the most important training data (the so-called support vectors), whose number does not grow exponentially with the number of training data. In other words, SVM is able to automatically select the number and the parameters of the basic functions according to the complexity of a function to be estimated but independent of the dimensionality of training data. Up to now, the use of SVM for dynamics modeling and identification has not been exploited much, especially when experimental implementation is concerned. In this paper, we present our study in dynamic-model identification using SVM, for enhancing the haptic display of the operating feel in using VR for medical training applications.

This paper is organized as follows. In Section II, we present the SVM-based friction modeling method. In Section III, some experimental results in identifying frictions are given. Section IV summarizes the conclusions drawn from the research work.

II. SVM-Based Friction Identification

A. SVM Algorithm

The SVM algorithm has its origin in the theory of statistical learning. Here, we present its algorithm via our identification case study. See [12] for more details about the theory. Assume that f denotes the relationship between the contact friction force F and a multidimensional input vector x (such as velocity v and normal force p) through the mapping $f : x \mapsto F = f(x)$. Here, for positive and negative velocities, the mapping will be treated in the same way, but the models will be given separately. In the examples presented in this paper, we assume positive velocity. We trivially assume that $f(x)$ evolves over some bounded set $\Omega \subset \Re$. Given the training data $D = \{(x_j, F_j)\}_{j=1}^{N}$, where $F_j = f(x_j)$ for each j and N is the number of the training data points, the identified friction model $\hat{F} = \hat{f}(x)$ can be obtained by seeking the solution of the following regularization problem:

$$\min_{\bar{f}\in H} R_{\rm reg}(\bar{f}) = L\sum_{i=1}^{N} c(F_i, \bar{f}(x_i)) + \frac{1}{2}\langle \bar{f}, \bar{f}\rangle_H \qquad (1)$$

in a reproducing kernel Hilbert space (RKHS) H defined by kernel $K(\cdot,\cdot)$ [13]. The first term in $R_{\rm reg}(\bar{f})$ is the cost of the training error, in which $c(F, \bar{f}(x))$ is the loss function measuring the error we make when predicting the friction force F by $\bar{f}(\cdot)$ at some input x. The second term is a stabilizer that reflects

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the effort for smoothing. $L > 0$ is a regularization constant to make a tradeoff between the training error and the smoothing constraint. The kernel $K(\cdot,\cdot)$ is a (strict) positive definite function defined over $\Omega \times \Omega$, that is, for any $x_1, x_2, \ldots x_3 \in \Omega$, the matrix $\lfloor K(x_i, x_j) \rfloor$ is (strict) positive definite. In addition, we assume that K has the expression in the form of

$$K(x_1, x_2) = \sum_{n=0}^{\infty} \phi_n(x_1)\phi_n(x_2) \tag{2}$$

where $\{\phi_n(x)\}_{n=0}^{\infty}$ is the set of linearly independent functions defined over Ω. A typical example of $K(\cdot,\cdot)$ is a radial basis function (RBF) in the form of

$$K(x_1, x_2) = \exp\left(-\frac{(x_1 - x_2)^2}{2\sigma^2}\right) \tag{3}$$

where $\sigma > 0$ is a radial width parameter. From the property of RKHS, given a kernel K in the form of (2), $\bar{f}(x)$ can be described in the following form:

$$\bar{f}(x) = \sum_{n=0}^{\infty} \alpha_n \phi_n(x) + b \tag{4}$$

for any $\alpha_n,\, d_n,\, b \in \Re$ equipped with the scalar product

$$\left\langle \sum_{n=0}^{\infty} \alpha_n \phi_n(x) + b, \sum_{n=0}^{\infty} d_n \phi_n(x) + b \right\rangle_H = \sum_{n=0}^{\infty} \alpha_n d_n. \tag{5}$$

To obtain a solution of the above regularization problem (1), we choose the ε-insensitive loss function

$$c(F, \bar{f}(x)) = \left|F - \bar{f}(x)\right|_\varepsilon$$

where $|\cdot|_\varepsilon$ is the Vapnik's ε-insensitive norm defined as

$$|F - \bar{f}(x)|_\varepsilon = \begin{cases} 0, & \text{if } |F - \bar{f}(x)| < \varepsilon \\ |F - \bar{f}(x)| - \varepsilon, & \text{otherwise.} \end{cases} \tag{6}$$

Substituting (4)–(6) into (1), we obtain

$$\min_{\bar{f} \in H} R_{\text{reg}}(\bar{f}) = L \sum_{i=1}^{N} |F_i - \bar{f}(x_i)|_\varepsilon + \frac{1}{2} \sum_{i=1}^{\infty} \alpha_n^2. \tag{7}$$

As the ε-insensitive norm is hard to handle mathematically, the above minimization is transformed into the following equivalent problem:

$$\min_{\bar{f},\xi,\xi^*}, R_{\text{reg}}(\bar{f}, \xi, \xi^*) = L \sum_{i=1}^{N} (\xi_i + \xi_i^*) + \frac{1}{2} \sum_{i=1}^{\infty} \alpha_n^2 \tag{8}$$

subject to the constraints

$$\begin{aligned} F_i - \bar{f}(x_i) &\le \varepsilon + \xi_i \\ \bar{f}(x_i) - F_i &\le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* &\ge 0 \end{aligned} \tag{9}$$

where ξ and ξ^* in (8) denote the slack vectors $[\xi_1, \xi_2, \ldots, \xi_N]^T$ and $[\xi_1^*, \xi_2^*, \ldots, \xi_N^*]^T$, respectively. Applying Lagrangian multipliers to this constrained optimization problem (8) and (9), we can obtain the identified friction model

$$\hat{f}(x) = \sum_{i=1}^{N} \partial_i K(x_i, x) + m \tag{10}$$

where ∂_i $(i \in 1, \ldots N)$ and m are parameter values obtained by solving the optimal problem. The corresponding ∂_i is nonzero only when the distance of the training points from the target is no less than ε. These training points are called support vectors. This friction identification method is referred to as SVM-based identification method. If the kernel is linear, the identified friction model can be expressed as

$$\hat{f}(x) = \pi \cdot x + m \tag{11}$$

where π is a constant obtained by solving the optimization problem.

B. *Friction Identification Examples*

Friction is an important dynamics for incorporation into the virtual environment to increase the reality. Yet, it is still hard to find a universally applicable model. For different materials, the parameters in the friction model change accordingly. It is therefore desired that the friction model be identified for particular applications. Here, we present three cases in friction identification: hard object, soft object, and needle puncture.

1) Hard Surface Friction Identification: Previous studies show that dynamics friction is related to the normal force applied to the surface. Experiments have also proved that the dynamics structure of this relationship is linear for hard surface contact. When using SVM-based friction identification algorithm, we can take advantage of this prior knowledge by choosing a linear kernel. The learning data pairs are "pressure $\left(x = [p]^T\right)$ and friction F ." By solving the optimization problem (8) and (9), the friction model is given as

$$\hat{F}(p) = \sum_{i=1}^{N} \partial_i p_i p + m.$$

2) Soft Surface Friction Identification: If the deformation of the soft material is not large, we can assume that the friction-pressure relation for a constant velocity is linear. Based on this assumption, the soft material friction identification procedure is given as follows.

1) Identify the friction-pressure function by identifying the parameters π, m in (11) at some constant velocity v.
2) Record the π, m, v data.
3) Choose a different velocity value and repeat step 1 and 2.
4) After a set of training data (π_i, m_i, v_i) is obtained, identify the $\langle v, \pi\rangle$, $\langle v, m\rangle$ relationship function in the following two steps.
   a) Choose a kernel. Here, we chose the Gaussian RBF kernel.
   b) Estimate the $\langle v, \pi\rangle$, $\langle v, m\rangle$ function $\bar{\pi} = f(v)$, $\bar{m} = f(v)$.

After the above steps, the friction-pressure-velocity relationship is obtained. Given velocity and pressure, we can first obtain

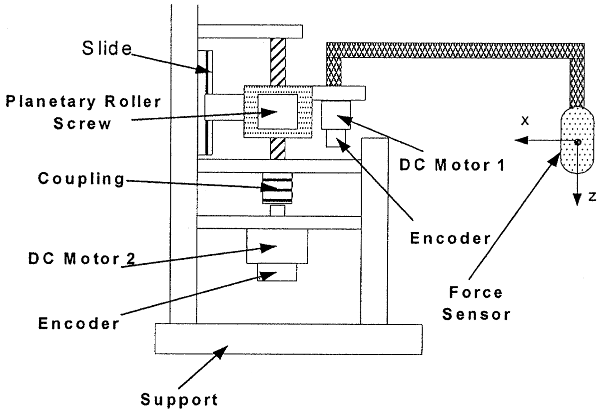

Fig. 1. Schema of the experimental setup.

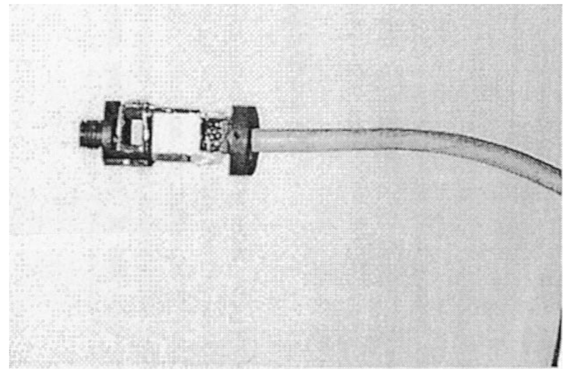

Fig. 2. Force sensor structure.

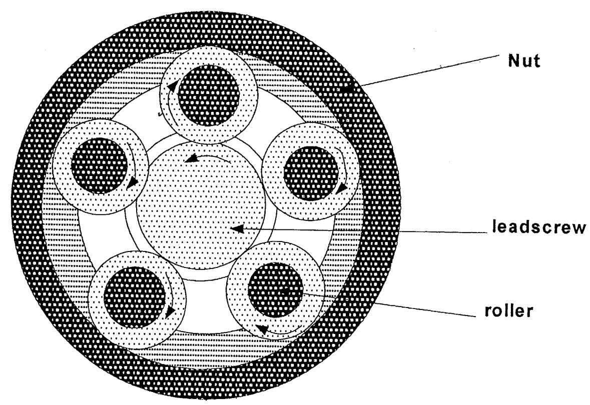

Fig. 3. Cross section of the PRS.

the corresponding π, m, and then compute the friction by (11) using the identified values of π, m.

3) Needle Puncture Dynamics Identification: A simple example involving dynamics interactions in surgical training is the puncturing operation using a needle. Here, we assume no prior knowledge about the puncturing dynamics model. To identify the model, we just use the SVM as a universal learning machine. The identification procedure is given as follows.

- Choose the Gaussian RBF as the kernel. The input is the needle's displacement and velocity $x = [s, v]^T$.
- Acquire the training data.
- Measure the dynamics input neglecting the mass of the needle. The measured output is the resistant force F_{mea}.
- Apply SVM algorithm to identify the dynamics model $\hat{F} = \hat{f}(x)$.

III. Experiments

In this section, we first present the experimental system setup and then show the experimental results corresponding to the three cases described above.

A. Experimental Setup

The experimental system was designed for dual use as a device for acquiring data for the identification purpose and as a haptic interface for subsequent force display purpose. The system setup simulates a simplified human finger exploring an unknown environment. It has two degrees of freedom: a rotational degree and a linear motion degree. The schema are illustrated in Fig. 1. The "finger" includes a three-dimensional (3-D) force sensor with an aluminum cover at the tip.

The force sensor can measure 3-D forces simultaneously. A picture of the sensor head is given in Fig. 2. Mechanically, the force sensor consists of three pairs of flat steel plates. The stiffness of each pair of plates is made low in only one direction so that it is sensitive to deformations in this direction. Three pairs of strain gauges are attached to the sensitive surfaces to measure the deformations which are related to the forces being experienced. The measurable force range in each direction is – 2 kg–2 Kg, with linearity errors less than 0.5% of the full span.

To achieve an accurate conversion of the rotational motion of a motor to the linear motion of the first degree of motion of the device, a special planetary roller screw (PRS) was employed. The principal components of the PRS are lead-screw, rollers, and nut as shown in Fig. 3. The features of this kind of structure include: large power increase, high efficiency, high position accuracy, high input speed, and low wear. The pitch of the PRS is 0.166 mm and its stroke is 35 mm.

The closed loop control of the two motion degrees of freedom is developed on a dSPACE controller. The dSPACE DS1103 PPC Controller Board is used here for the implementation of the high-speed multivariable digital controllers and real time simulations. The controller board is directly plugged into the host PC using the ISA bus as a backplane. This setup provides a platform for the measurements for the identification and for the haptic display as well.

B. Hard Surface Friction Identification

The first experiment conducted involved contact between the mechanical finger and a hard surface of an aluminum plate as shown in Fig. 4. For the contact surface friction identification, the training data pair is the "pressure force and friction force" which were measured by the z-axis and y-axis channel of the force sensor. In this experiment, we controlled motor 1 to move the "finger" along the surface of the aluminum plate following a sine wave trajectory. The normal force was controlled via motor 2.

Using the method described in Section II-B, we obtained the friction model training data. Here, we chose $L = 10^{11}$, $\varepsilon =$

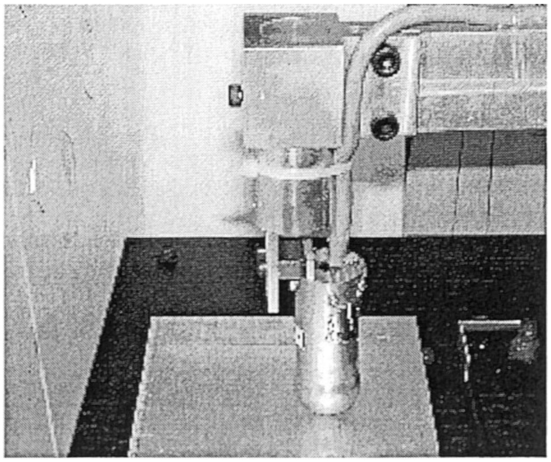

Fig. 4. Hard contact experiment.

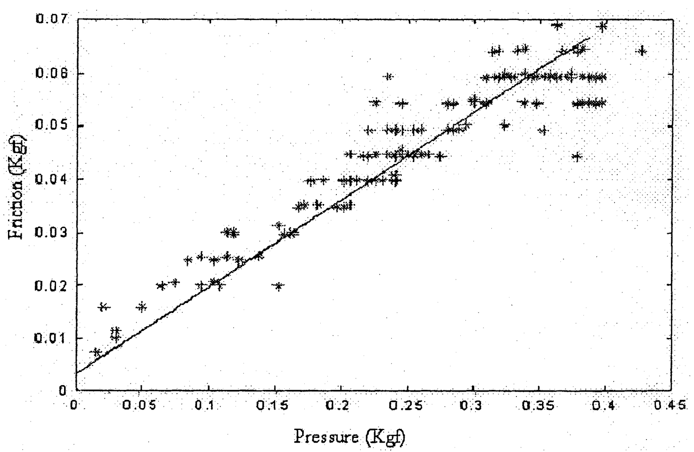

Fig. 5. Identified friction in hard contact.

0.003 for 31 training data pairs (P_i, F_i). Solving the optimization (8) and (9), we can obtain the identified friction model

$$\hat{F} = 0.1647P + 0.0033. \tag{12}$$

The training data and the identified result are also given in Fig. 5. An error of about 0.0033 is observable at the origin. This error results from the imperfect measurement hardware of the system but is considered acceptably small.

C. Soft Surface Friction Identification

The experimental setup for soft contact experiments is same as that for hard contact shown in Fig. 4, except that a sponge type of material is used in place of the aluminum plate. Following the procedures given in Section II-B, we conducted the experiments by first controlling motor 1 to move at a constant velocity along the soft material surface. Changing the pressure force by controlling motor 2, we obtained a set of pressure-friction training data for identifying the parameters π, m. Then, with a different velocity by controlling motor 1, the above was repeated. We used an optical encoder as the position sensor in the experiment. To obtain the velocity signal, we differentiated the position signal. This has a potential disadvantage of introducing

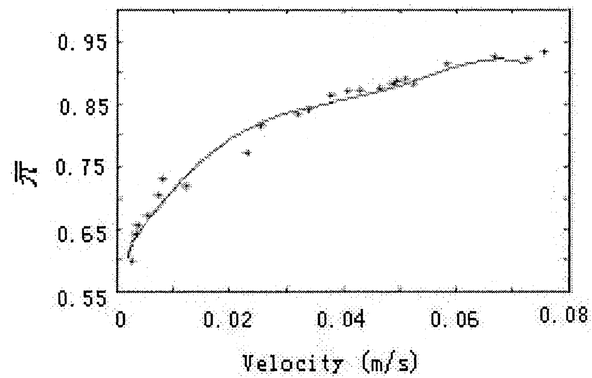

Fig. 6. Identified function for $\bar{\pi}$.

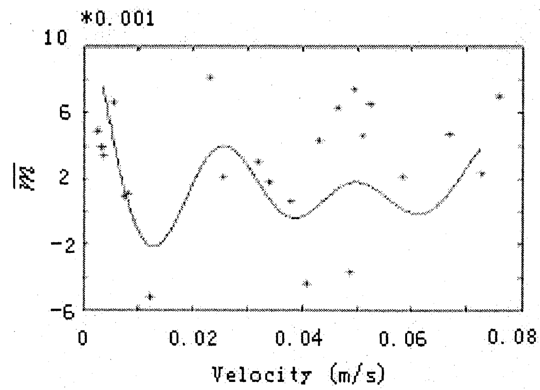

Fig. 7. Identified function for $\bar{m}$.

noise. To improve the velocity estimation, we used a high-resolution optical encoder. Furthermore, a digital filter is employed where the estimated velocity is computed as

$$\bar{\nu}(z) = \frac{z-1}{(\tau+T)z-\tau}x(z) \tag{13}$$

where x is the measured displacement, $\bar{\nu}$ is the estimated velocity, T is the sampling period, and τ is a small time constant.

Figs. 6 and 7 show the result of the identified function $\bar{\pi} = f(v)$ and , $\bar{m} = f(v)$.

After $\langle \pi, v\rangle$, $\langle m, v\rangle$ functions are identified, the soft material friction model can be constructed as a two-dimensional (2-D) function as shown Fig. 8, where the dynamic inputs consist of the velocity and pressure force.

This soft surface friction model was identified with only 56 support vectors from the 320 training data. For comparison, we also conducted the identification experiments using the same training data set but applying two traditional methods: the physical model (Columb + viscous) based method [9] and the RBF network-based method [11]. For the physical-model-based method, the Columb friction was given as proportional to the normal pressure and the viscous friction as proportional to the relative velocity. Using the least-mean-square technique, the Columb and viscous parameter values were identified as 0.7648 and 0.8333, respectively. For the RBF network method, Matlab's Neural-Network Toolbox was used for the implemen-

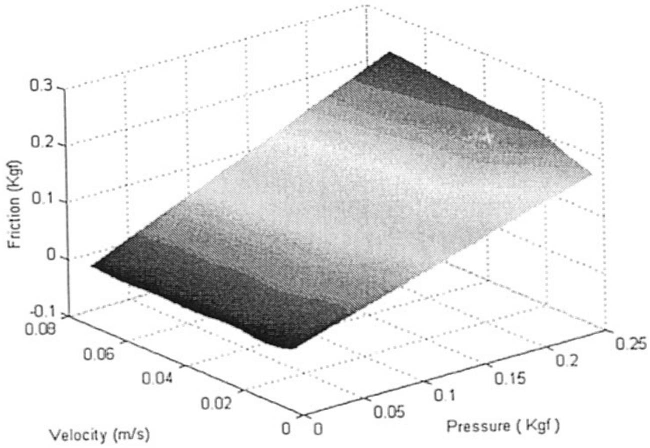

Fig. 8. Identified friction for a soft material.

TABLE I
EXPERIMENTAL COMPARISON FOR SURFACE FRICTION IDENTIFICATIONS

Friction modeling method	AISE value	$\left\|F_{mea} - \hat{F}\right\|_\infty$
SVM	2.3445E-4	0.0369
Columb+ Visious method [9]	3.5190E-4	0.0415
RBF Network [11]	3.1868E-4	0.0451

tation. To compare the three friction identification algorithms, the average integral squared error (AISE), defined as

$$\text{AISE} = \frac{1}{T}\int_0^T e^2 dt$$

with a trajectory observation duration T of 10 s was used as the assessment index, where e is the estimation error. The sampling step used was 0.2 s. Table I shows the results obtained by the three identification methods. Here, $|F_{\text{mea}} - \hat{F}|_\infty$ is taken as the identification error bound, and F_{mea} is the actual measured friction force. The AISE values shown in Table I indicate the advantages of our method over the other two. From the results, it can be inferred that using the traditional physical models such as the Columb + Viscous model here, it is difficult to fully characterize the nonlinear nature in the friction model. This is overcome in our SVM-based method as indicated by the improved AISE in the results. The RBF network method seems to improve on the physical model in its modeling capability. However, its resulting AISE is still worse than the SVM-based method. This confirms the advantage of SVM over a traditional neural network when only limited training data are available. The increased error bound in the RBF network method can be attributed to the overfitting by this method as we observed at some data point in our tests. In general, the SVM based method offers a more acceptable identification results than the traditional methods.

D. Needle Puncture Dynamics Identification

In this experiment, a needle is attached to the tip of the force sensor as shown in Fig. 9. The test object is a portion of fresh

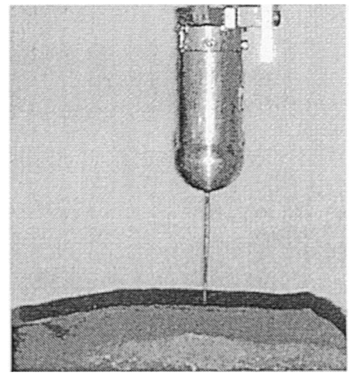

Fig. 9. Needle puncture experiment.

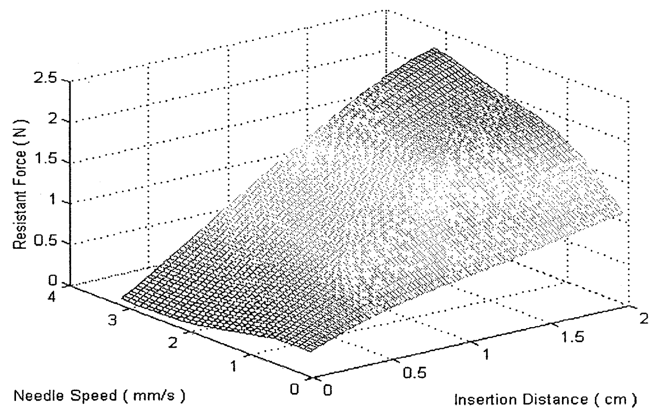

Fig. 10. Identified puncture dynamics.

TABLE II
EXPERIMENTAL COMPARISON FOR NEEDLE PUNCTURE MODEL IDENTIFICATION

Friction modeling method	AISE value	$\left\|F_{mea} - \hat{F}\right\|_\infty$
SVM	8.9225E-3	0.2369
RBF Network	1.5179E-2	0.3647

meat. The resistant force in the puncture is measured from the z-axis reading of the force sensor. The insertion distance is measured using the encoder reading. The velocity is estimated by the aforementioned approach via (13). Motor 2 controls the insertion of the needle. Following the procedures given in Section II-B, we identified the puncturing dynamics, with the results given in Fig. 10.

From the identified result, we can see that the resistant force is nonlinear in relation to the insertion distance and the needle speed. This 2-D model can be given by only 98 support vectors from 350 training data, making it suitable for the high updating rate required in haptic force display. The identified function turned out to be quite continuous, thanks to the filtering effect by the ε-insensitive function. We also experimented with the same training data but using traditional methods. As the needle puncture force is highly nonlinear in relation to both the insertion distance and needle speed, traditional parameter based physical model is unsuitable. The results of using the RBF network method are given in Table II for comparison with our SVM method. The results in the AISE and error bound values again

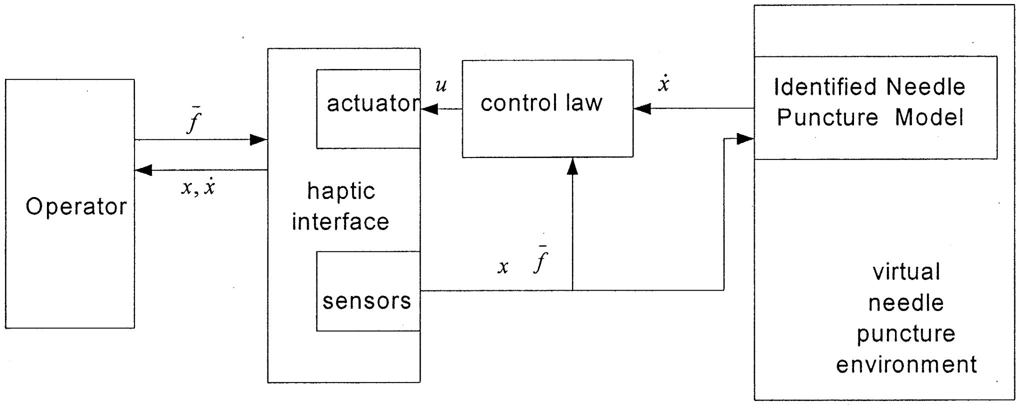

Fig. 11. Control schema for the haptic interface.

show that the SVM-based method outperforms the RBF network based method in the identification.

E. Haptic Display of Identified Dynamics

As an implementation case study, we incorporated the identified needle puncture dynamics model in a virtual environment to test the training on a VR system. In this experiment, the haptic display is implemented using the same 2-degrees-of-freedom device we developed and used in our needle puncture dynamics identification tests. However, in this case, the needle is to be held and moved by the operator.

The system is a desktop VR system. The computer is a PC installed with a graphics acceleration card, under Windows NT system. The haptic display device is controlled by the dSPACE Controller. The software programming is based on Visual C++ using OPENGL Graphics Lib. The core part of the haptic display system is the identified needle puncturing dynamics model which serves as the reference output for the haptic display control system as shown in Fig. 11. Different methods can be used for dealing with the contact forces including impedance control [14]. Here, we implemented admittance control scheme to suit the hardware adopted in the system. When using the haptic display, the operator applies a force to the haptic interface. The control law here uses the measured interaction force between the needle and the operator's hand, and derives the control signals based on the desired motion output, to drive the actuator to produce the corresponding motion. The virtual contact force is displayed to the operator via the haptic interface so that he feels as if he is puncturing some real flesh.

Fig. 12 shows the force-displacement history experienced by the operator during a typical virtual puncturing process. This force-displacement relationship is the control results using the identified needle puncture model. The identified friction was highly nonlinear and affected by the needle puncturing speed.

With a traditional finite-element method (FEM), it is very difficult to incorporate even some simplest dynamics and it is even harder to obtain the model parameters describing the properties of the material in the model accurately. The identified model via SVM offers its advantage in its easy and efficient implementation in VR for high-rate haptic display. For traditional identification algorithms, such as neural networks, large training data sets are needed, which may not be easily feasible in real applications. The SVM-based method on the other hand provides a more flexible way for practical applications by removing such a need. Finally, the self-learning capability of SVM allows improvement of the identified model whenever new experimental data are available.

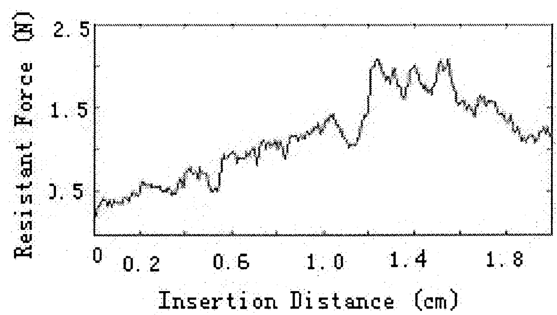

Fig. 12. Forces experienced during virtual puncturing.

IV. Conclusion

This paper presents an approach for identifying dynamics models using the SVM regression algorithm, which overcomes the limit of traditional identification methods that require large training data sets. With SVM-based identification, the model is only recorded by the information of the support vectors, whose number does not grow exponentially with the number of training data. This algorithm can automatically select the number and the parameters of the basic functions according to the complexity of dynamics function to be estimated but independent of the dimensionality of the training data. The identified dynamics models were incorporated into a virtual environment for authentic display of the dynamics interactions between the operator and the virtual objects. Our implementation indicates that the SVM regression algorithm provides a useful tool for dynamics model identification with sparse training data compared with traditional methods. The experiments show that by incorporating the experimentally identified dynamics for haptic display, the operator's immersion in a virtual environment can be significantly improved. The learning capability of SVM will allow easy incorporation of updated/improved dynamics models in the training platform whenever new experimental data are available.

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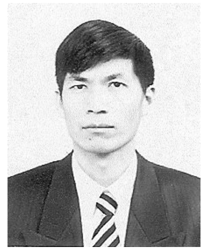

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