Environmental Impedance Estimation and Imitation in Haptics by Sliding Mode Neural Networks

Baris Yalcin and Kouhei Ohnishi, *Fellow, IEEE*

Department of System Design Engineering, Keio University
3–14–1, Hiyoshi, Kouhoku, Yokohama, Kanagawa, 223–8522, Japan
barisyalcin@sum.sd.keio.ac.jp, ohnishi@sd.keio.ac.jp

Abstract— **Due to the future perspective to reproduce highly nonlinear characteristics of the contacted environment exactly in the absence of environment, especially in haptics research, and also due to providing high robustness and stability of robot control systems during environmental contacts, ensuring precision in environmental impedance estimations and storing environmental impedances are imperative studies.**

In this paper impedance is considered as a nonlinear mapping from position and velocity to force. This paper utilizes a sliding mode control theory based neural network, which is proposed to be used as a fast and fussy online environmental impedance & stiffness estimator and imitator by relating position and velocity dimension to force dimension. In the end, validity of online impedance estimation method and how a neural network can turn to be the model of contacted environment (imitation) are going to be shown by the experimental results. As a future perspective, continuation of this research is going to result in exact environmental impedance reproduction.

I. Introduction

Robot contacts to environments have been investigated by a wide range of researchers belonging to various backgrounds such as haptics and teleoperation. In order to make sure the robustness and stability of control techniques, such as force or compliance control, environment information is required. Some of the fundamental researches about environmental impedance estimations and control are in the literature. Kelvin-Voigt linear model [1] is widely used for environment estimations however it is vulnerable to soft environment contacts [2]. Impedance control is improved by integration of real time adaptive estimation of environment [3]. Hunt-Crossley nonlinear model [2] is proposed for development of contact models especially for improvement in soft contacts. Neural networks are made to represent nonlinear compliance [4]. Time-varying environment stiffness is controlled by neural nets [5]. Since stiffness matrices largely define environmental characteristics at low speeds, grasping behavior is explained by stiffness [6, 7].

Neural networks are known as their fast processing and generalization capabilities. In addition, they are used for making memories [8] and learning [9]. Generalization capacity versus network size is investigated in [10] and neural network system identification is presented in [11]. Sliding mode control technique which is well known with its robustness can be used in order to improve closed loop system integration of neural networks in the view point of stability [12] because when placed into a feedback system, neural networks can take unexpected behaviors [13]. A sliding mode error learning neural controller for robot manipulators is proposed in [14]. This network is utilized in this paper for impedance and stiffness estimations as well as environment imitation.

One of the main attentions of this paper is given to haptics field which strongly engages environment. Bilateral control techniques have been suggested for this field. A hybrid position-force controller considering reproducibility and operationality concepts is in [15] and a multilateral acceleration controller is in [16]. These controllers are force sensorless mechanisms and utilize disturbance observers which can obtain wider bandwidths than the usage of force sensors [17, 18]. In addition, stability and transparency [19] and vivid touch sensation [20] are investigated.

In this paper, environmental impedance is considered as a nonlinear mapping from position and velocity dimensions to force dimension. The utilized learning mechanism does not require any preliminary information about the environment as well as it does not require an explicit dependency on the control mechanism. Error back propagation based learning is conducted online via input (position and velocity) - output (force) pairs called online teaching data. It is shown that environment impedance can be learnt by sliding mode based neural algorithm and the stiffness which is one of the basic features of an environment can be identified during learning. The bilateral control mechanism that provides data during real time experiment to the neural network is hybrid position force controller.

Section II presents the sliding mode neural network [14], basically. Then in section III, bilateral controller is explained. In section IV, the blueprint of neural impedance estimator and bilateral controller is shown. In section V, real time experiment results are stated. Conclusions and future work are summarized in section VI.

II. Sliding Mode Feedback Error Learning Neural Network

We propose that a neural network can be a candidate to represent environment during or in the end of bilateral haptic manipulation. This representation can be observed under the condition that robot-environment interaction based position, velocity, acceleration and the other derivative terms of position information are provided to the

1-4244-0136-4/06/$20.00

neural mechanism.

$$F_{env}(t) = NeuralNetwork(x(t), \dot{x}(t), \ddot{x}(t), \ldots) \quad (1)$$

where $F_{env}(t)$ is the environmental reaction force information that neural network try to predict. Since in many cases acceleration and the other terms are so small and negligible, additionally neural networks can estimate and generalize data well, (1) can be modified as (2):

$$F_{env}(t) = NeuralNetwork(x(t), \dot{x}(t)) \quad (2)$$

So, it can be assumed that environmental impedance estimation is dependent on position and velocity parameters. For online estimation and imitation of environment impedances, a fast and robust algorithm is necessary. Sliding mode learning algorithm based neural networks are known as robust and fast convergent structures. Firstly proposed by Topalov and Kaynak [14] and used for control of robot manipulators, the following learning algorithms based on the explanations below can be utilized for environment predictive network which consists of p inputs, n hidden layer neurons and 1 output:

$W1(t)_{(n*p)}$: Weight matrix of the time varying connections that connect input layer neurons to hidden layer neurons. Each element of the matrix $w1(t)_{ij}$ means the connection weight of the neuron i from its input j.

$W2(t)_{(n*1)} = [w2_1(t)...w2_n(t)]^T$: Weight vector of the time varying connections that connect hidden layer neurons to output layer neurons.

$X(t)_{(p*1)} = [x_1(t) \ldots x_p(t)]^T$: Time varying input signals vector such as position and velocity.

$T_H(t)_{(n*1)} = [\tau_{H1}(t)...\tau_{Hn}(t)]^T$: Output signals vector of the neurons in hidden layer.

$NNF(t)$: Time varying scalar output signal of the network.

$f(.)$: Hidden layer activation function. This function is nonlinear, differentiable and monotonously increasing. The neuron in the output layer has a linear activation function.

$S(t)$: Sliding difference between predicted neural network force output and environmental reaction forces.

$$S(t) = NNF(t) - F_{env}(t) \quad (3)$$

Using sliding mode approach, zero value of learning error coordinate $S(t)$ is defined as a time varying sliding surface:

$$S(t) \longrightarrow 0 \quad (4)$$

The primary aim of the neural network is to drive $S(t)$ to zero in time in order to accomplish a total resemblance of the network output to the environmental reaction force. For any time, $S(t) = 0$ is the condition that the neural network model is totally trained to become a nonlinear predictor to obtain the desired response by imitating the nonlinearity of the environment.

Sliding motion takes place for all t in some nontrivial semi open subinterval of time $[t, t_f) \subset (-\infty, t_f)$ under the condition [14] :

$$S(t)\dot{S}(t) < 0 \quad (5)$$

The learning algorithms for the network weights have been derived in such a way that the sliding mode condition is enforced [14].

$$\dot{w}1_{ij} = -\frac{w2_i x_j}{X^T X} sign(S(t))\alpha \quad (6)$$

$$\dot{w}2_i = -\frac{\tau_{H_i}}{T_H^T T_H} sign(S(t))\alpha \quad (7)$$

where α is the learning rate. Here are the other terms and derivations related with (6, 7):

$$\tau_{H_i} = f(\sum_{j=1}^{p} w1_{i,j} x_j) \quad (8)$$

$$NNF(t) = \sum_{i=1}^{n} w2_i \tau_{H_i} \quad (9)$$

$$sign(S(t)) = \frac{S(t)}{|S(t)| + \sigma} \quad (10)$$

where σ is the threshold value to prevent chattering phenomena.

In accordance with the convergence analysis in [14], finite time t_f convergence of the above learning algorithm occurs (11) if derivative of system inputs (12), derivative of hidden layer outputs (13), derivative of desired environment force output (14) and connection weights (15, 16) are bounded by some finite constants, and if learning rate is chosen sufficiently large by considering these boundaries.

$$t_f \leq \frac{|S(0)|}{\alpha - B_{\dot{F}_{env}} - nB_A B_{W1} B_{W2} B_{\dot{x}}} \quad (11)$$

$$\left\| \dot{X}(t) \right\| \leq B_{\dot{x}} \quad \forall t \quad (12)$$

$$f'(\sum_{j=1}^{p} w1_{i,j} x_j) \leq B_A \quad \forall i, j \quad (13)$$

$$\left| \dot{F}_{env} \right| \leq B_{\dot{F}_{env}} \ \forall t \quad (14)$$

$$\|W1_i(t)\| \leq B_{W1} \ \forall t \quad (15)$$

$$|W2_i(t)| \leq B_{W2} \ \forall t \quad (16)$$

In a controlled bilateral system, bounded input bounded output stability is observed. Considering this type of stability, neural network inputs (position and velocity) are going to be bounded. In addition, magnitudes of weight matrices are also considered as bounded because of physical constraints [14].

In order to show that neural networks can estimate environmental reaction force and become the imitator of environment, and also in order to be coherent with the future perspective of this research, precise tactile data reproduction, we are going to deal with haptic mechanisms.

III. Four-Channel Bilateral Controller

In this section, we are going to discuss the haptic mechanism and control, briefly. In order to accomplish bilateral control, as two goals, reaction force from the environment must be felt by the user (master) and user driven path (position) must be correctly followed by the robot during the environmental contact.

$$F_m + F_s = 0 \quad (17)$$
$$X_m - X_s = 0 \quad (18)$$

where $F_{m,s}$ means user (master) and environment (slave) force parameters as well as $X_{m,s}$ means master and slave position parameters.

As seen from (17, 18), both force and position must be bilaterally controlled.

$$\ddot{x}_m^{ref} = C_p(s)(X_s - X_m) + C_f(s)(F_m - F_s) \quad (19)$$
$$\ddot{x}_s^{ref} = -C_p(s)(X_s - X_m) + C_f(s)(F_m - F_s) \quad (20)$$

where C_p is the position controller and C_f is the force controller of the system. Since acceleration dimension is the common dimension of position and force, controller equations are based on acceleration as a reference.

$$C_p(s) = K_v s + K_p \quad (21)$$
$$C_f(s) = K_f \quad (22)$$

where position control is based on velocity control gain K_v and position control gain K_p. Force control is only based on a force control gain K_f.

During environment force observation, instead of force sensors reaction force observer technique [17] is used in this research (28). Reaction force observer estimates force only with position sensor. Reaction force observation is based on disturbance observer technique which is widely used for suppression of disturbances in systems. Both techniques utilize low pass filters (27) to estimate reaction forces and system disturbances. Total load force F_L exerted on a system can be calculated as follows:

$$F_L = F_{int} + F_{ext} + F_{coulomb} + D\dot{X} \quad (23)$$

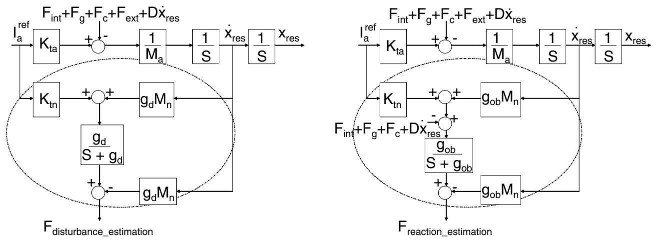
where F_{int} is the representation of coriolis, centrifugal and gravity terms, F_{ext} is reaction force and $D\dot{X}$ is viscous friction. Total disturbance force F_{dis} can be calculated as in (24):

$$F_{dis} = F_L + \Delta M\ddot{X} - \Delta K_t I_a^{ref} \quad (24)$$
$$\Delta M = M_a - M_n \quad (25)$$
$$\Delta K_t = K_{ta} - K_{tn} \quad (26)$$

where M_a is the actual inertia, M_n is the nominal inertia, K_{ta} is the actual torque coefficient and K_{tn} is the nominal torque coefficient.

Disturbance and reaction force observation equations of the system are shown in (27) and (28), respectively. Cut-off frequency of the disturbance and reaction force observers are represented by g_d and g_{ob}, respectively.

$$F_{dis.est} = \frac{g_d}{s + g_d} F_{dis} \quad (27)$$
$$F_{reac.est} = \frac{g_{ob}}{s + g_{ob}}(I_a^{ref} K_{tn} + g_{ob} M_n \dot{X} - F_{int} - F_g - F_c - D\dot{X}) - g_{ob} M_n \dot{X} \quad (28)$$



(a) Disturbance observer (b) Reaction force observer

Fig. 1. Disturbance and reaction force observation structures for bilateral control

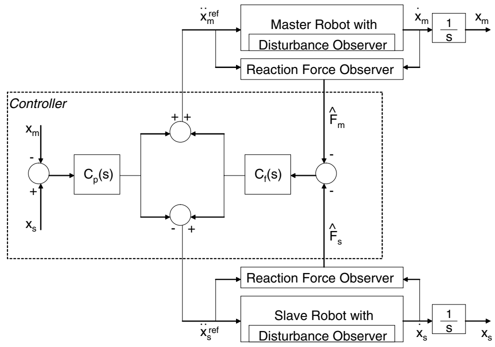


Fig. 2. Four-Channel bilateral controller based on disturbance and reaction force estimators

The proposed disturbance and reaction force observers and bilateral controller can be seen in Fig. 1(a), (b) and Fig. 2, respectively.

IV. Neural Learning Structure in Bilateral Control

To handle data and identify the process during haptic action, neural networks can be utilized like a plug-in tool as shown in Fig. 3. In this scheme, at each sampling time neural network estimation is compared with real environment reaction force and the error affects the connection weights. This is back-propagation error learning. The other inputs to the neural system are velocity and position data which is obtained by position sensor. Sliding mode algorithm drives the sliding error between neural force estimation and environment reaction force into a manifold and makes the network represent environment correctly. Learning rate determines the convergence speed of the network. Neural network does not intervene to the bilateral control algorithm.

If position-velocity dimensions and force dimension can be related during haptic action, then the stiffness k of the environment can be obtained easily (29).

$$k = \frac{\partial F}{\partial X} \quad (29)$$

After the convergence time of the network, force-position relation and characteristics, environmental impedance, stiffness and characteristics are stored and identified in neural networks. Online stiffness estimation can be done as in

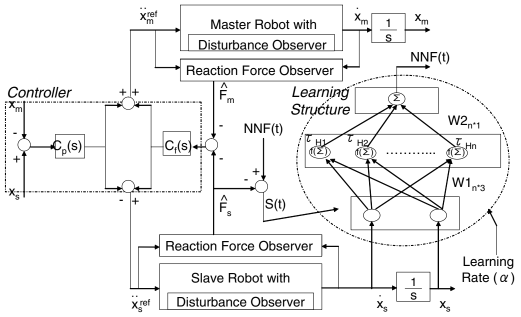


Fig. 3. Haptic Neural Blueprint

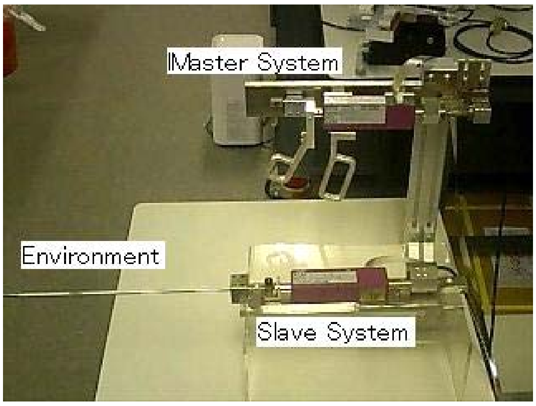


Fig. 4. Experiment setup

(30):

$$k = \frac{\partial NNF}{\partial X} \tag{30}$$

Although the system relates velocity and position dimensions to force dimension and it can also resemble viscosity, in this paper performance evaluation of the network for different environments is based on stiffness comparisons.

V. Real Time Experiment

A. Experiment Setup and Parameters

In Fig. 4, the experimental setup of the haptic mechanism is shown. In this 1 degree of freedom forceps robot, master is driven by human operator via a handle. Robot to environment contact occurs at nipper which is located at the end of system slave side. Human operator feels the environment as he is touching it. Master and slave sides are actuated by 1 linear motor for each. The control software is written in C language under RT-Linux. Sampling time is 0.1 ms. Initial distance between nipper and environment is arbitrary, however surface of the environment is located in between nipper arms. In the experiments sponge, silicone gel and steel are used as different real environment examples. The controller parameters for each of these environments have the same value.

Disturbance and reaction force observation frequencies are 191 Hz. In addition, a sinusoidal human input force of $6.5sin(4.725t - (\pi/2)) + 6.5$ is inputted to the system.

TABLE I

Real time experiment parameters

Control Parameter	Value
K_p	10000
K_v	200
M_n	0.12 kg
K_{tn}	10.83
K_f	1
g_{ob}	1200 rad/s
g_d	1200 rad/s
# of neurons	12
# of neurons (Fig. 13)	26
learning rate (α)	2.8
initial weights	$\in [-1, 1]$
threshold (σ)	0.015

B. Experiment Results

In the experiments, a sinusoidal input is applied as a human input for all environments as seen in Fig. 5(a), 6(a) and 7(a). Before evaluating the experimental results, it should be mentioned that for such a sinusoidal input, the environment deformation could occur. This deformation result in different stiffness values for the same position-velocity input pairs. This may cause generalization of environmental properties by neural networks. Additionally, the obtained stiffness values also include the stiffness of the robot itself. On the other hand, if the generalization of the dimensional relation is not desired, then instead of sinusoidal force input, a linear force input can be given to the haptic system as shown in Fig. 12(a). Memorization of dimensional relation by the network for this type of an unrepeating unidirectional force input is carried out by computer simulation. In computer simulation, the neural network is trained by same input pairs until learning occurs.

It is shown that bilateral control of position and force has been accomplished for the three environments, as seen in Fig. 5, 6 and 7. For steel, although it is a very stiff material, stability is highly preserved during contact. So, vivid force sensation is established. In addition, neural network real time environment reaction force estimation errors for silicone gel, sponge and steel can be seen in Fig. 8(a), 8(b) and 9(a), respectively. The errors are close to zero after a very short time. This implies that neural network predicts environment reaction forces. On the other hand, to identify this sensation quantitatively, neural network memorized stiffness estimations for silicone gel, sponge and steel can be seen in Fig. 10, 11 and 9(b), respectively. The stiffness values during contact with the silicone gel, sponge and steel are estimated as 6000 N/m, 8000 N/m and 62000 N/m, respectively. However, since steel is a very stiff material after an ignorable positional penetration, 0.5×10^{-4} m, its stiffness suddenly increases to 12×10^4 N/m as seen in Fig. 9(b). On the other hand, stiffness of silicon gel, since it is a viscous material, does not increase sharply at the time of contact as seen in Fig. 10(b). In addition to these, sponge shows an increase in stiffness proportional to position. Sponge is not a very stiff material but when the penetration depth increases, it shows very stiff characteristics. Additionally, the neural network environment memorization is extended to two different materials regarding the possibility of non-homogeneous environments as shown in Fig. 13, by computer assisted memorization. In this type of learning, firstly, the force, position and velocity data of the two different haptic actions are loaded and then this data is inputted to the neural network. Data shown in Fig. 12 belongs to silicone gel, the data for sponge is obtained in the same manner. Neural network is trained until it represents both of the environments. In our approach, we shift the positional values of the sponge to prevent the neural system from conflict. As a result of the experiments, it can be concluded that neural networks estimate environment reaction force correctly during real time experiment. According to the results of the trained neural network function, environmental stiffness as well as impedance characteristics have been successfully stored.

VI. Conclusion

In this paper, stiffness and environmental impedance estimation during haptic processes have been investigated. One of the targets of this research is to find the exact function which represents environment. It is shown that sliding mode neural networks, with their fast processing capabilities, estimated the environment reaction force during real time haptic process and act as a nonlinear environment function which relates position and velocity parameters to force parameter. The control mechanism of the system is a four channel bilateral controller. Neural network acts like a plug-in tool and do not intervene to control system. The neural network environment memorization is evaluated by stiffness comparison. This is important in the viewpoint of reproduction of environment characteristics in the absence of environment. Neural network environment estimation and imitation are shown to be succeeded by real time experiments.

Acknowledgments

This research is supported in part by the Ministry of Education, Culture, Sports, Science and Technology of Japan under Grant-in-Aid for scientific research (A), 17206027, 2005.

References

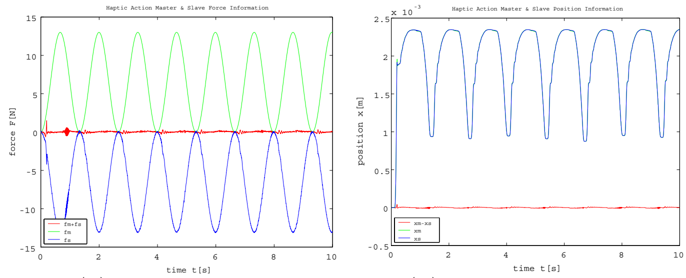
[1] W. Fluggë, *Viscoelasticity,* Waltham, MA: Blaisdel, 1967.

[2] K. Hunt and F. R. Crossley, "Coefficient of restitution interpreted as damping in vibroimpact," *ASME J. Appl. Mech.*, vol. 42, pp. 440–445, June 1975.

[3] L. J. Love and W. J. Book, "Environment estimation for enhanced impedance control," *Proc. Int. Conf. Robot. Autom.*, vol. 2, pp. 1854–1859, Nagoya, Japan, May 1995.

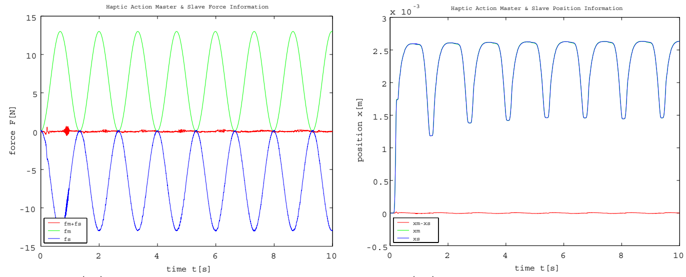
[4] H. Asada, "Teaching and learning compliance using neural nets: representation and generation of non-linear compliance," *Proceedings of the 1990 IEEE International Conference on Robotics and Automation*, pp. 1237–1244, Cincinnatti, Ohio, USA, vol. 2, May 1990.

[5] S. Jung and T. C. Hsia, "Analysis of nonlinear neural network impedance force control for robot manipulators," *Proceedings of*



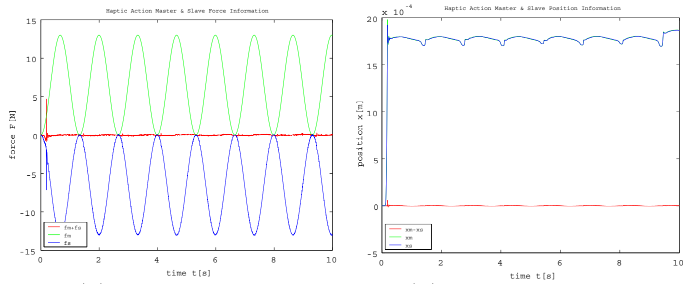
(a) Force control (b) Position control

Fig. 5. Force Position control of haptic mechanism for silicone gel



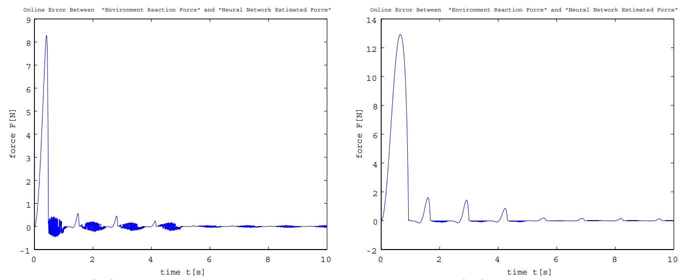
(a) Force control (b) Position control

Fig. 6. Force Position control of haptic mechanism for sponge



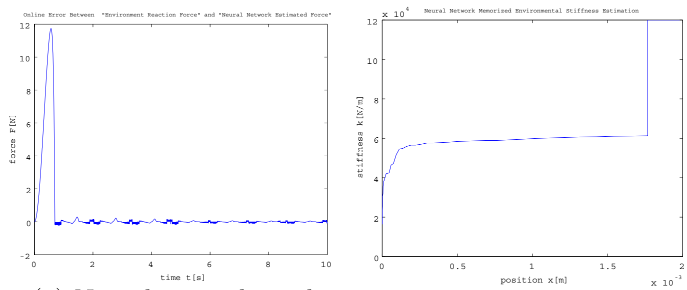
(a) Force control (b) Position control

Fig. 7. Force Position control of haptic mechanism for steel



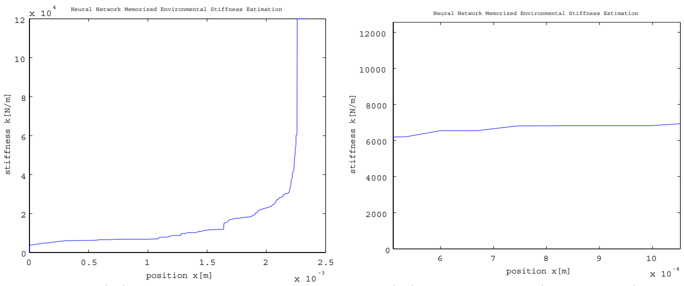
(a) Silicone gel (b) Sponge

Fig. 8. Neural network environment reaction force online estimation error



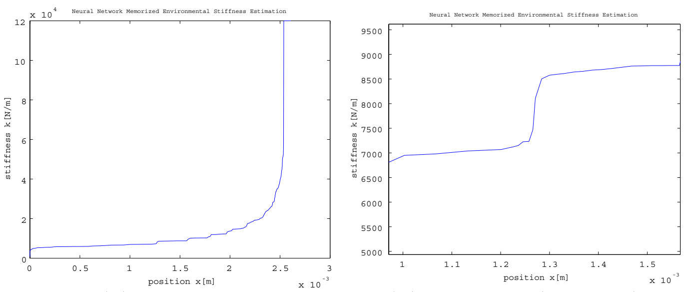
(a) Neural network steel reaction force estimation error (b) Neural network memorized stiffness of steel

Fig. 9. Steel reaction force error and memorized stiffness



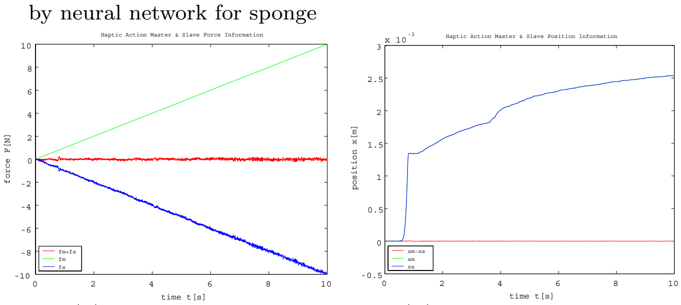
(a) Stiffness (b) Stiffness (zoomed)

Fig. 10. Stiffness based evaluation of memorized dimensional relation by neural network for silicone gel



(a) Stiffness (b) Stiffness (zoomed)

Fig. 11. Stiffness based evaluation of memorized dimensional relation by neural network for sponge



(a) Force control (b) Position control

Fig. 12. Force position control of silicone gel with unidirectional increasing force input

the 1998 IEEE International Conference on Robotics and Automation, vol. 2, pp. 1731–1736, Leuven, Belgium, May 1998.

[6] H. Asada, *Studies on Prehension and Handling by Robot Hands with Elastic Fingers. PhD thesis,* Kyoto University, April 1979.

[7] M. R. Cutkosky and I. Kao, "Computing and controlling compliance of a robotic hand," *IEEE Transaction on Robotics and Automation*, vol. 5, no. 2, pp. 151–165, April 1989.

[8] A. N. Michel and J. A. Farrell, "Associative memories via artificial neural networks," *IEEE Control Systems Magazine*, vol. 10, pp. 6–17, April 1990.

[9] M. Kawato, Y. Uno, M. Isobe, R. A. Suzuki, "Hierarchical neural network model for voluntary movement with application to robotics," *IEEE Control Systems Magazine* , vol. 8, no.2, pp. 8–16, 1988.

[10] E. B. Baum and D. Haussler, "What size net gives valid generalization?," *Neural Computation*, vol. 1, pp. 151–160, 1989.

[11] K. S. Narendra and K. Parthasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Trans. Neural Networks*, vol. 1, pp. 4–27, March 1990.

[12] M. O. Efe and O. Kaynak, "Stabilizing and robustifying the learning mechanisms of artificial neural networks in control engineering applications," *Int. J. Intelligent Systems* , vol. 15, no. 5, pp. 365–388, May 2000.

[13] F. L. Lewis, S. Jagannathan and A. Yesildirek, *Neural Network Control of Robot Manipulators and Nonlinear Systems* , Taylor & Francis, London, 1999.

[14] A. V. Topalov and O. Kaynak, "A sliding mode strategy for adaptive learning in multilayer feedforward neural networks with a

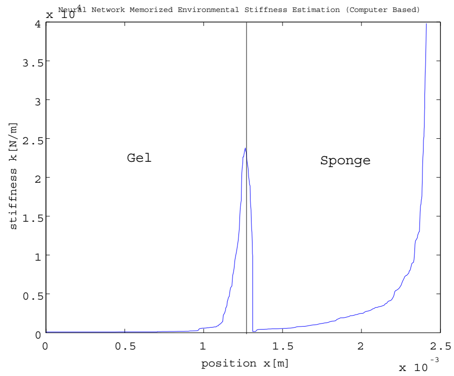


Fig. 13. Stiffness based evaluation of computer assisted memorization of dimensional relation for silicone gel and sponge

scalar output," *IEEE Trans. on Systems, Man, and Cybernetics*, vol. 2, pp. 1636–1641, oct. 2003.

[15] W. Iida and K. Ohnishi, "Reproducibility and operationality in bilateral teleoperation," *Proc. of the 8th IEEE Int. Workshop on Advanced Motion Control*, pp. 217–222, Kawasaki, Japan, 2004.

[16] S. Katsura, Y. Matsumoto and K. Ohnishi, "Realization of law of action and reaction by multilateral control," *IEEE Trans. on Industrial Electronics*, vol. 52, no. 5, pp. 1196–1205, 2005.

[17] T. Murakami, F. Yu and K. Ohnishi, "Torque sensorless control in multidegree-of-freedom manipulator," *IEEE Trans. on Industrial Electronics*, vol. 40, no. 2, pp. 259–265, 1993.

[18] K. Ohnishi, M. Shibata and T. Murakami, "Motion control for advanced mechatronics," *IEEE/ASME Trans. on Mechatronics*, vol. 1, no. 1, pp. 56–67, 1996.

[19] D. A. Lawrance, "Stability and transparency in bilateral teleoperation," *IEEE Trans. on Robotics and Automation*, vol. 9, no. 5, pp. 624–637, 1993.

[20] S. Katsura, K. Ohnishi, "Feedback of Reaction Force in Haptics," *IEEE International Conference on Industrial Technology ICIT '03*, MARIBOR, Tutorial, pp. TU13-TU20, 2003.