FUZZY- NEURAL NETWORK BASED INTELLIGENT ROBUST CONTROL SYSTEMS

Yoshishige Sato

Tsuruoka National College of Technology
Tsuruoka City, Yamagata Prefecture, 997-8511, JAPAN

ABSTRACT

The intelligent robust controls such as a neural network based control for mechatoronic positioning servo systems have been researched actively in recent years because the mechanism design could not cope with the advanced requirements. This paper proposes a novel robust fuzzy-neural network based intelligent robust control for the mechatoronic positioning servo systems that have nonlinear characteristics such as friction, backlash, variations of load and system parameters, and unknown disturbances. Computational simulation results and experimental results for one degree-of-freedom positioning system are shown to confirm the validity of the proposed controller.

Keywords: Fuzzy control, neural network, intelligent robust , intelligent control

INTRODUCTION

The intelligent robust controls for mechatronic servo systems such as a neural network based control, fuzzy rule based control, and fuzzy-neural network based control have been researched actively in recent years because the mechanism design could not cope with the advanced requirements in mechatronic Servo system [1]-[3]. A two degree-of-freedom control has been widely adopted in mechatronic servo system because it has a feedforward compensator and a feedback compensator and permits us to design the tracking characteristics for the desired input and the closed loop characteristics for the disturbance and measurement noise independently. However, the two degree-of- freedom control could not reduce the tracking error caused by the modeled dynamics and the intermittent disturbance adequately [4], [5].

This paper proposes a novel robust fuzzy-neural network based control for mechatronic servo systems that have nonlinear characteristics such as friction, backlash, variations of load and system parameters, and unknown disturbances. The proposed fuzzy-neural network based intelligent robust control is composed of three compensators: a feedforward compensator that has the inverse dynamic model of the servo system by neural networks, a feedback compensator of position and velocity, and a nonlinear deviation compensator by fuzzy neural networks. The feedforward compensator based on the neural network and the feedback compensator based on the optimal regulator have been presented in early researches [6]-[9]. However, it is a structural feature that the proposed control has a nonlinear deviation compensator formed by the fuzzy-neural networks, of which input are a position deviation and its time derivative, such that it contributes to reduce the deviation generated by modeling error, friction and unknown disturbances adaptively. By adding the output of the nonlinear deviation compensator to the output of feedforward compensator, the position deviation is reduced. This paper presents the validity of the proposed control through computational simulations and experiment for one degree-of-freedom servo system with large friction, backlash, and variance of parameters.

FUZZY NEURAL NETWORK BASED ROBUST CONTROL SCHEME

The proposed fuzzy-neural network based control scheme consists of two elements: a) the feedforward compensation which has inverse dynamics of the PD controlled plant based on neural networks; and b) the nonlinear deviation compensator based on the fuzzy neural networks. The block diagram of the proposed control system is shown in Fig. 1. This control system is a two degree-of-freedom system, which permits us to design the tracking characteristic for the desired input and the closed loop characteristic for the disturbances separately. Its aim is the complete tracking for the desired input and the perfect removal of the effect of disturbances. Moreover, it decreases the modeling error and the tracking error generated by intermittent disturbances. This control system would do the groundwork for the robust-control system against the nonlinear characteristics such as friction, variations of load and system parameters, and unknown disturbances in mechatronic position servo system.

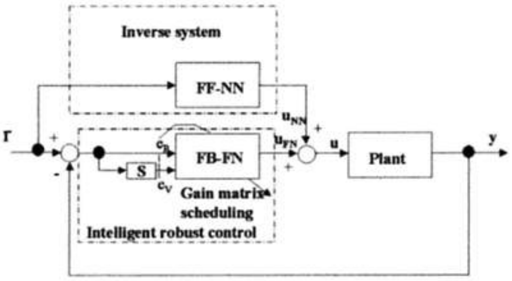


Fig. 1 Block diagram of FN robust control

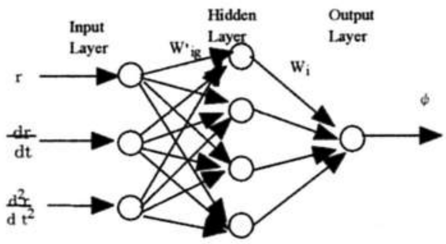
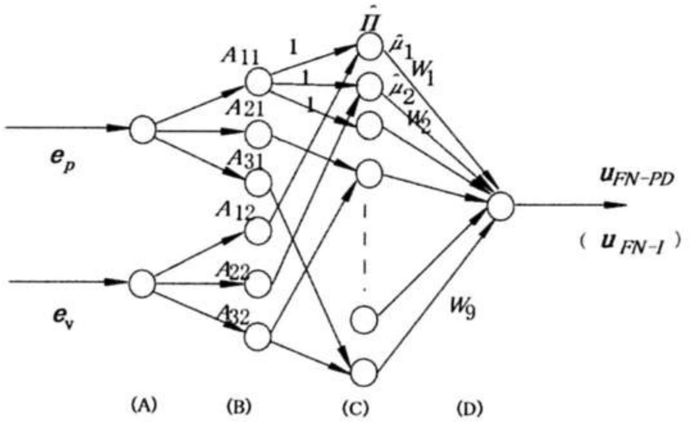
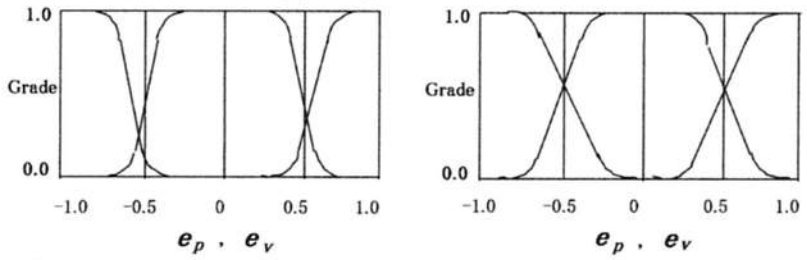


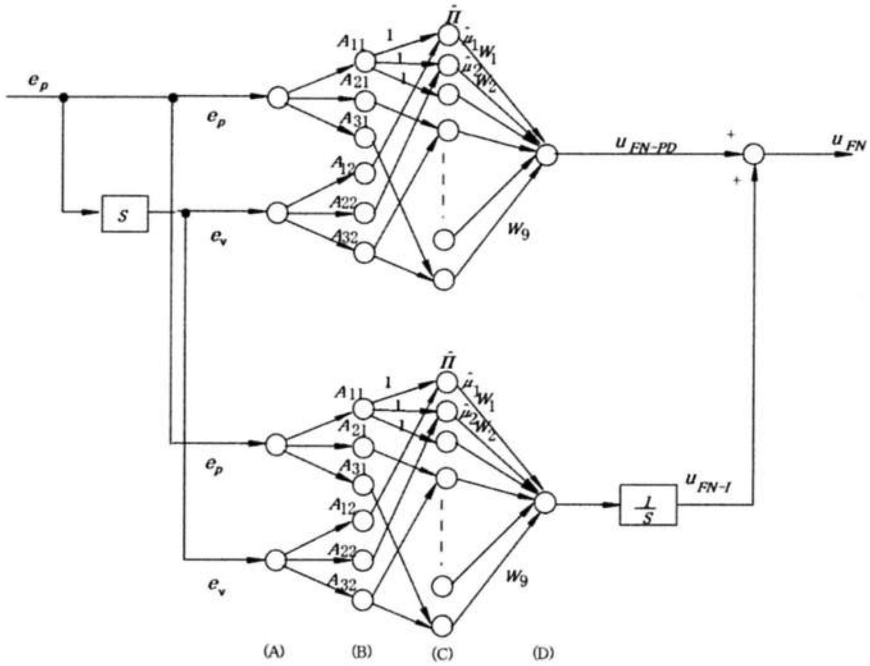
Fig. 2 Feedforward neuralnetwork compensator



(1) Fuzzy -Neural Network



(2) Membership function (FN-PD) (3) Membership function (FN-I)



(4) Architecture of the fuzzy-neural network

Fig. 3 Fuzzy-neural network nonlinear deviation compensator

FEEDFORWARD COMPENSATION BASED ON NEURAL NETWORKS

By ignoring nonlinear characteristics, the plant can be liberalized as follow:
Fig. 2 Feedforward neural network compensator

$$J\frac{d^2y(t)}{dt^2} = -k_v\frac{dy(t)}{dt} - k_p y(t) + k_p u(t) \tag{1}$$

where $u(t)$ is the input, $y(t)$ is the output of the position, k_p and k_v are the position and velocity feedback gains, respectively. The inverse dynamics of the plant is represented by

$$u(t) = r(t) + \frac{k_v}{k_p}\frac{dr(t)}{dt} + \frac{J}{k_p}\frac{d^2r(t)}{dt^2} \tag{2}$$

where $r(t)$ is the desired position. This model expresses the basic characteristics of a positioning servo system. But the actual model has differences in the values of the inertial moment, and has the nonlinear element that cannot be represented by the second order model. It is evident that the inverse dynamics given by (2) include the modeling error. However, a learning of inverse dynamics of actual servo system is executed through the neural networks shown in Fig. 2. The neural networks consist of 3 layers, 3 inputs, 4 intermediate units, and 1 output. The learning is done by the back propagation method using the positions of input and output and their time derivatives. After the learning, it is expected that the responsibility of the system rises through feedforward input of this network.

ROBUST GAIN SCHEDULING BASED ON FUZZY NEURAL NETWORKS

The deviation between the desired position and the output position is caused by the modeling error and unknown disturbances. The nonlinear deviation compensator based on the fuzzy neural networks reduces the deviation adaptively. A scheme of the fuzzy neural network is shown in Fig. 3(1). This fuzzy neural network is 2 inputs, 1 output and 4 layers; A is input layer; B and C are middle layers; and D is output layer. Each element of B layer generates an output of a membership function formed by a gauss function as shown in Fig. 3(2), and this part is called a premise. C layer outputs an adaptation that is reasoned based on the fuzzy rule, and this part is called a consequent. According to the structure of the neural networks with the fuzzy rule, this is called fuzzy neural networks. The fuzzy neural networks can be applied learning by the back propagation (BP) method and be related to the fuzzy reasoning rule by the devisal of the connection of the layered neural network.
This system is composed of a F-NN which has 2 inputs, 1 output, and 4 layers. The input has a position error e_p and a velocity error e_v. The input is the direct input of the plant. The fuzzy part divides (division into 9) the input space, and then generates adaptation:

$$\mu_i = A_{i_1}(e_p)A_{i_2}(e_v)\; i=1, 2,\ldots,9, i_1, i_2=1,2,3 \tag{3}$$

Adaptation is normalized as follows:

$$\overline{\mu}_i = \frac{\mu_i}{\sum_k \mu_k} \tag{4}$$

The fuzzy rule for No.1 is as follows:

$$R^i\text{: IF } e_p \text{ is } A_{i_1} \text{ and } e_v \text{ is } A_{i_2} \text{ THEN } y=f_i(e_p e_v) \tag{5}$$

And the reasoning is given by:

$$u_{FN} = \sum_{i=1}^{9} \overline{\mu}_i f_i(e_p, e_v) \tag{6}$$

f_i is assumed as:

$$f_i = k_{iI} \int e_p dt + k_{ip} e_p + k_{iv} e_v \tag{7}$$

But f_i is a gain, as shown in Table 2:

Both e_p and e_v are small: PID control

e_p is not small, e_p is different from e_v: P control

(When $| e_p |$ is big, the speed feedback which makes the value of $k_{ip}e_p$ small is removed)

For the left cases, this Neural Network learns gain in the following Neural Network in order to generate PD control.

By this composition, additional control rule can be constructed. In addition, this control rule is adapted to error.

Neural Network learns the control gain.

The learning is performed under the condition that the square of the position error becomes the smallest. And then,

$$E_p = \frac{1}{2} e_p^{\,2} \tag{8}$$

$$k_{ij} = w_{ij}^{\,2} \tag{9}$$

And then, $k_{ij} = w_{ij}^{\,2}$ is settled in order to get the following expression:

$$k_{ij} \geq 0 (j = I, p, v)$$

And the renewal quantity is calculated as follows:

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} \tag{10}$$

Table 1 Control rules		e_v		
		Positive big	Small	Negative big
e_p	Positive big	P	PD	P
	Small	PD	PID	PD
	Negative big	P	PD	P

$$= -\eta \frac{\partial E_p}{\partial e_p} \frac{\partial e_p}{\partial u_{FN}} \frac{\partial u_{FN}}{\partial f_i} \frac{\partial f_i}{\partial k_{ij}} \frac{\partial k_{ij}}{\partial w_{ij}} = -\eta\, e_p \frac{1}{\sum_{l=1}^{9} \overline{\mu}_l {w_{lj}}^2}\, \overline{\mu}_i\, e_j\, 2w_{ij}$$

$$= -\frac{2\eta\, \overline{\mu}_i e_p\, e_j w_{ij}}{\sum_{l=1}^{9} \overline{\mu}_l {w_{lj}}^2} \quad j{=}I,p,v \tag{11}$$

where w_i is a connection weight. The connection weights are learned by the BP method, in which initial values are set zero. The teaching data in the learning are the input and output of a PD controller, which is the same block diagram given by Fig. 1 on condition that the nonlinear deviation compensator is changed to the PD compensator. The proportional and differential gains are adjusted such that the output position follows the desired feasibly.

Fig. 4 FN-GS gain controller C(s) is calculated as follows:

$$C(s) = \sum_{i=1}^{9} C_i(s) = \sum_{i=1}^{9} \mu_i (K_{ip} + K_{iv} s + K_{iI} \frac{1}{s}) \tag{12}$$

Gain matrix of FB-FN is shown Fig. 6.

After learning, the adaptation plays a role as the dynamic compensator, and the output adapted to position and velocity errors is obtained. This means that a compensation output that is suitable to errors is computed. Hence, it is expected that proposed fuzzy neural network based control system is robust for the disturbances and the parameter variations.

It is calculated a gain of FN-GS to show with Fig. 5.

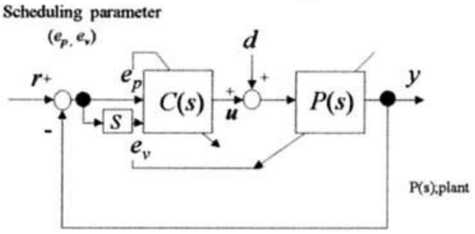


Fig. 4 Block diagram of F-N controller

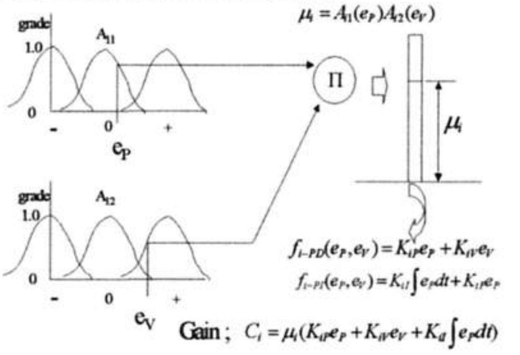


Fig. 5 Calculation of FN-GS gain

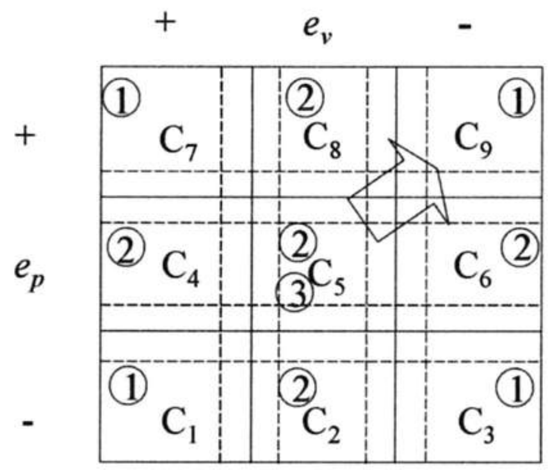


Fig. 6 Gain matrix of FB-FN

COMPUTER SIMULATION

Computational simulation has been done for one degree-of-freedom positioning servo system with high nonlinear characteristics by using MATLAB software. The desired position trajectory is given by the sine wave. Three control methods are examined for comparisons; (1) PID control, which is most widely used approach in mechatronic servo system: (2) Neural network (NN) control, which make feedforward input based on the learned inverse dynamics of the plant: (3) Proposed fuzzy neural network (FN) based control. The main parameters of the simulation are given in Table 1. The following parameter set is adopted; $K_A = 2$, $K_v = 2.5$.

The simulation results of system responses in case of nominal plant parameters by the two control methods are shown in Fig.1. In this simulation, PID gains are adjusted such that the position error is minimized, that is, $K_P = 3$, $K_I = 1$, and $K_D = 1.5$. This figure shows that the response of the FN control is better than that of the FF control, but the response of PID control is better than the other methods.

The simulation results of system responses in case of adding the random disturbance to the plant are shown in Fig.7. This shows that a membership function of a former incident part used by proposed method as a robust filter clearly.

The simulation results of system responses in case of step disterbance are shown in Fig. 8. Proposed method is provided a good reply result of standing characteristic. This shows that the most suitable gain of adaptation is realized clearly for PID control of system and model type gain scheduling conventionally.

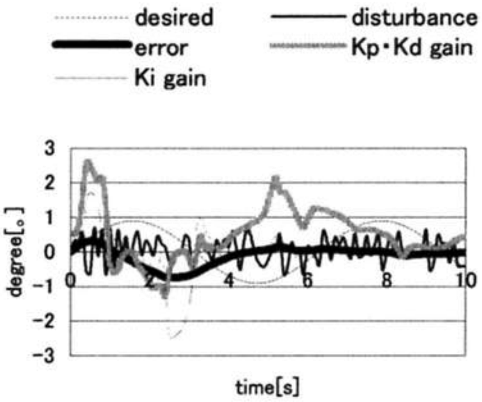


Fig. 7 Response for FN-GS control on condition of random disturbance

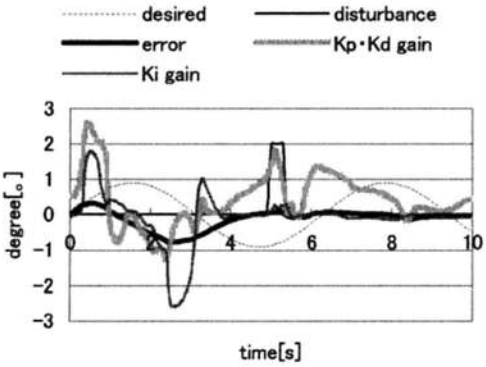
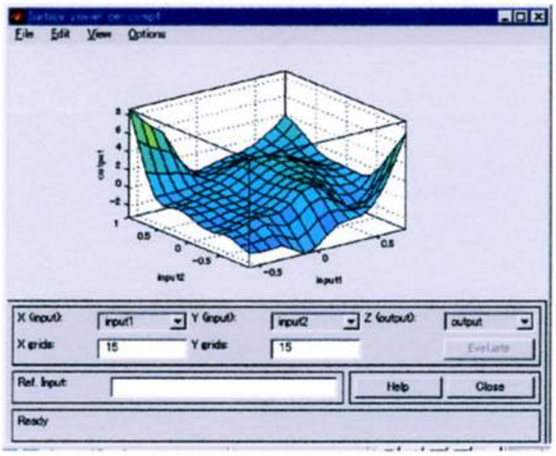
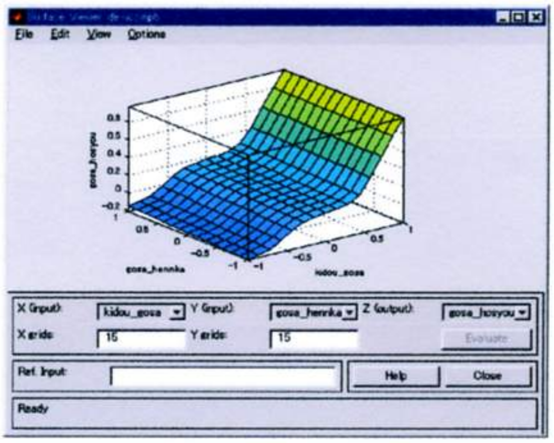


Fig. 8 Response for FN-GS control on condition of step disturbance



X (input): input1
Y (input): input2
Z (output): output
X grids: 15
Y grids: 15
Ref. Input:
Ready

(1) $U_{FN\text{-}PD}(e_P,\ e_V)$



X (input): kidou_gosa
Y (input): gosa_hennka
Z (output): gosa_hosyou
X grids: 15
Y grids: 15
Ref. Input:
Ready

(2) $U_{FN\text{-}PI}(e_P,\ e_V)$

Fig. 9 Control surface of FN-GS controller

EXPERIMENT

We used only the first joint of a small 6 axis robot in order to confirm the effectiveness of the control method we proposed, the robot was used as a one degree of freedom system.

The experiment was done under the following conditions:Sampling time: Ts=2ms; Speed gain: Kv=3; NN learning frequency: N=5000: F-N learning Frequency: N=50; Command signal: T(t): Sine wave (Amplitude: 30deg; Frequency: 1Hz). As shown in Fig.9 looking at the reply signal, obtained by the feed forward NN compensator, the phase delay is improved.

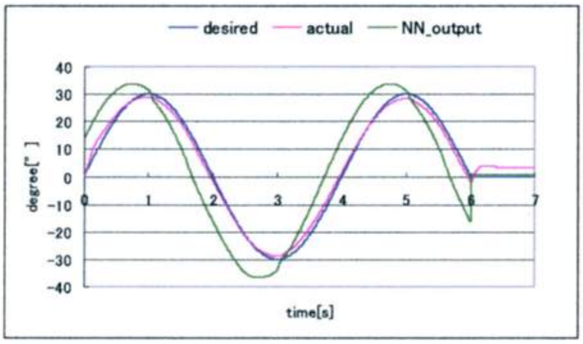
This implies that the NN follows aim orbit effectively. However, a routine deviation ocurs due to friction in peak.

On the other hand, as is shown in the response signal of Fig.11 the nonlinear deviation compensator containing the fuzzy-neural network, reduces moderately the modeling error due to the NN of the feed forward compensator, and the deviation due to friction. According to these facts, enough performance improvement is observed.

Moreover, looking at the reply signal which shows the change of the output of fuzzy–neural network having disturbance, an output signal of F-NN which follows the aim signal is generated

As Fig.12 shows, it is proved that the fuzzy–neural network is robust against disturbances.

Fig. 10 Experimental system robot



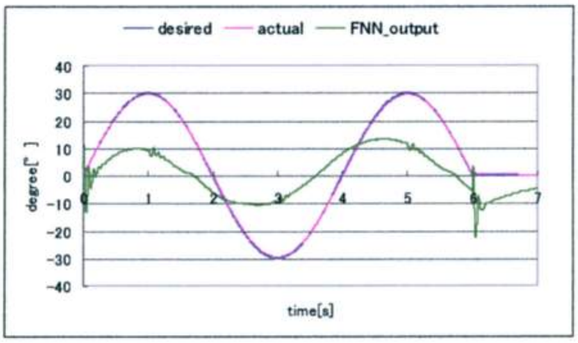


Fig. 11 Response of NN control method **Fig. 12 Response of F-N control method**

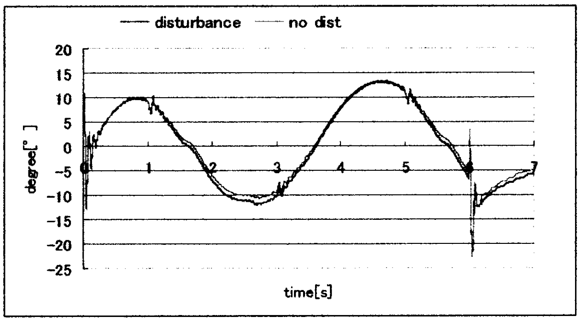


Fig. 13 Response of F-N control on condition of disturbance

CONCLUSION

A novel Fuzzy-neural network based control system has been proposed for the mechatronic positioning servo systems with highly nonlinear characteristics. The proposed fuzzy-neural network based robust gain scheduling control is composed of two compensators: the feedforward compensator that has the inverse dynamic model of the servo system by neural networks and the nonlinear deviation compensator constructed by fuzzy-neural networks. It is proved through the computer simulation and experiment that the proposed control method is robust against parameter variations and intermittent disturbances compared with the PID control, which is adopted commonly, and the neural network control.

It is concluded that the proposed nonlinear deviation compensator reduces the position trucking error remarkably.

REFERENCES

[1] T. Yabuta, T. Yamada: "Force Control for Robot Manupulators using Neural networks," JRSJ, Vol. 9 No. 2, pp. 224~231 (1991)
[2] A. Shimokawabe, et al. : "Control Performance of Two-stage Positioning System with Intelligent Control Methods, "JSME (C), Vol. 66 No. 648 (2000)
[3] Noguchi, Yoshida, et al. : "The Control of the PUM Type Robot with a neural network and the adaptive control," No.15 JRSJ
[4] K, Onishi: "Robust Motion Control by Disturbance Observer", JRSJ, Vol. 11 No. 4 pp. 486-493 (1993)
[5] Umeno, Hori: "Constitution of Two Free Angles Robust Servo System and Application to the Motion Control of Manipulator," JSEE, 110-11 D 1163-1170 (1990)
[6] S. N. Huang, K. Ktan, and T. H. Lee: "Adaptive Friction Compensation using Neural Network Approximations," IEEE TRANNCIONS ONSYSTEM MAN, AND CYBERNETICS-PART, Vol. 30 No. 4 (2000-11)
[7] M. Isogai, F. Arai, T. Fukuda: "Study about Vibration Control using Modeling of Flexible Multi-Linking System and Neural Network," JSME (C), 638 (1999-10)
[8] Kobayashi, Murata, Morisawa: "Fundamental Study about Adaptation to Oil Pressure Servo Mechanism of Neural Network," JSME (C), 638 (1990-10)
[9] R. Yoshino, H. Takahashi: "Vibration Control of Low Rigidity Legged Locomotion Robot by Filter Inclusion LQ Servo," JRSJ, Vol. 18 No.1, pp. 110-119 (2000)