International Journal of Fuzzy Logic and Intelligent Systems, vol. 7, no. 4, December 2007 pp. 267-273

Implementation and Experiment of Neural Network Controllers for Intelligent Control System Education

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Abstract

This paper presents the implementation of an educational kit for intelligent system control education. Neural network control algorithms are presented and control hardware is embedded to control the inverted pendulum system. The RBF network and the MLP network are implemented and embedded on the DSP 2812 chip and other necessary functions are embedded on an FPGA chip. Experimental studies are conducted to compare performances of two neural control methods. The intelligent control educational kit(ICEK) is implemented with the inverted pendulum system whose movements of the cart is limited by space. Experimental results show that the neural controllers can manage to control both the angle and the position of the inverted pendulum systems within a limited distance. Performances of the RCT and the FEL control method are compared as well.

Key Words : Neural network controller, RCT, FEL, DSP, FPGA

1. Introduction

Nowadays, the word "Intelligence" has become a very important meaning to the systems, specially robot systems and mechatronics systems to satisfy endless human desires. The greediness of humans makes machines smart so that machines can serve humans in every manner.

Recently, there have been a lot of interests to develop intelligent robots that can think like humans, talk like humans, and behave like humans. However, the technology is far beyond from our expectation. Many efforts have been made to interpret human expressions as system representation for control systems to satisfy the given specification regardless of any environmental changes. Knowledge based control algorithms are one of them.

In the framework of control systems, intelligent control methods have been actively used to deal with uncertainties of the system to satisfy the desired goal. Neural network algorithms and fuzzy logics are two main tools for the online application to endow the intelligence to the system. Fuzzy logics are used as a main controller to directly minimize the error between the desired and the actual output by defining the optimal rules, while neural network is used as an auxiliary controller in association with the main PD or PID controllers to help minimizing the errors indirectly[1-8].

The ultimate goal of most of neural network control schemes and their modification schemes is to minimize output errors. The nature of minimizing errors yields two different schemes, a controller gain tuning scheme and a compensation scheme[9-11].

In the strategy of tuning methods, neural network is used to tune controller gains adaptively against system parameter variations. PID controller gains are updated by neural network outputs. In the strategy of the compensation method, neural network actually generates signals by learning algorithms to compensate for uncertainties in the nonlinear systems. A structural configuration of the compensation point yields different control schemes, the feedback error learning scheme (FEL) and the reference compensation technique scheme(RCT), which are well known control methods for neural network applications[12,13]. Ultimately, the purpose of two schemes is same to identify the inverse dynamics of the system. Studies of two schemes have been conducted in many applications such as robot position control and motor control.

Therefore, it is necessary to develop the test-beds of intelligent control methods to educate students in a graduate level as well as in an undergraduate level to satisfy demands from many areas. Intelligent control education becomes very important in not only theoretical aspects but also empirical aspects. Combining both the theory and the experiment helps students to understand the objectives better. As an initial step of the research, an inverted pendulum control system kit is developed.

In this paper, two neural network control schemes are studied and implemented on DSP boards to control the inverted

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Manuscript received Sep. 20, 2007; revised Dec. 10, 2007.
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This research was financially supported by the Ministry of Commerce, Industry, and Energy (MOICE) and Korea Industrial Technology Foundation (KOTEF) through the Human Resource Training Project for Regional Innovation and 2007 KOSEF Engineering scholarship program for graduates.

pendulum system built in the educational lab unit. The educational lab unit is in the progress of testing a variety of intelligent control algorithms including fuzzy logics. The graphic user display is designed to provide the interactive control facility in a PC so that students can learn and modify different control algorithms by performing experiments with ease. Multi-layered perceptron(MLP) networks and radial basis function (RBF) networks associated with different learning schemes are implemented to control the inverted pendulum along with the PID control method.

2. Neural network structure

2.1. Multilayered Perceptron Network(MLP)

One hidden layered feed-forward structure is shown in Fig.1. In general, for control applications, one hidden layered structure is used most for achieving the real time control performance. The hidden and the output layer are nonlinear. The nonlinear function of hidden units is the tangent hyperbolic function.

$$f(x) = \frac{1 - \exp(-x)}{1 + \exp(-x)} \qquad (1)$$

The output of the hidden layer is described as

$$O_j = f\left(\sum_{i=1}^{N_I} x_i w_{ij} + \theta_j\right) \qquad (2)$$

where x_i is the input value, w_{ij} is the weight between the input and the hidden layer, and θ_j is the bias weight. The output layer is described as

$$O_k = f\left(\sum_{j=1}^{N_{H1}} O_j w_{jk} + \theta_k\right) \qquad (3)$$

where w_{jk} is the weight between the hidden and the output layer and θ_k is the bias weight.

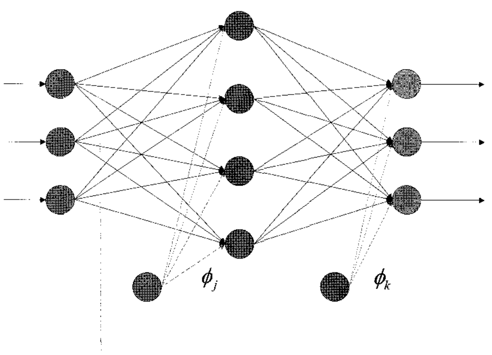

Figure 1. MLP neural network structure

2.2. Radial Basis Function Network

Fig. 2 shows the RBF network structure. It has only one hidden layer and the output layer is linear so that it has a much simpler structure than that of the MLP.

The nonlinear function for the hidden layer is given by the Gaussian function.

$$\phi_j(x) = \exp\left(-\frac{|X - \mu_j|^2}{\sigma_j^2}\right) \qquad (4)$$

where μ_j is the mean value and σ_j is the covariance.

Then the output can be calculated as

$$y_k = \sum_{j=1}^{N_H} \phi_j w_{jk} + \theta_k \qquad (5)$$

where w_{jk} is the weight value and θ_j is the bias weight.

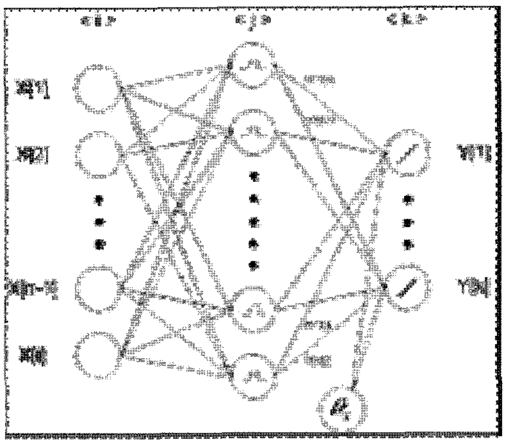

Figure 2. RBF neural network structure

3. Neural network control scheme

For neural network control applications, there are two different strategies to use neural networks. One is that neural network is used to optimize PID controller gains and the other is used to compensate for uncertainties in the system. Ultimately, the goal of both strategies is same to minimize output errors.

Here, in the framework of compensation strategy, two popular schemes available in the literature are presented, the feedback error learning scheme and the reference compensation technique scheme.

3.1 Feedback Error Learning Scheme

The feedback error learning scheme proposed by Kawato has the similar structure with the feed-forward control scheme that the output of the auxiliary controller is added to the output of the primary controller as shown in Fig. 3. The objective of the neural network is to generate signals to achieve the inverse dynamic control which leads to minimize the output errors[11].

The torque input is summed as

$$\tau = \tau_N + \tau_C \qquad (6)$$

where τ_N is the output from neural network and τ_C is the output of the controller.

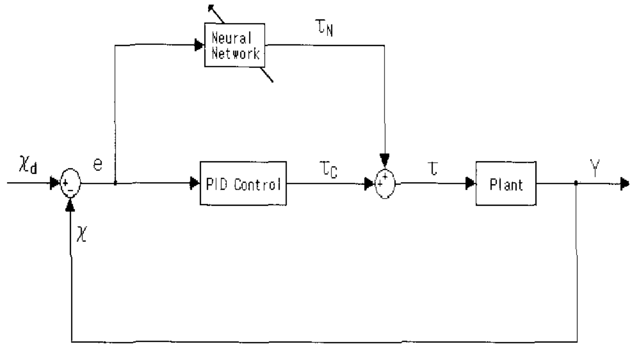

Figure 3. FEL control scheme

Let the system dynamics be as

$$\tau = f(x, \dot{x}, \ddot{x}) \tag{7}$$

Then the objective of the neural network is to generate the signal to satisfy the relationship for the inverse dynamics control objective.

$$\tau_C = \tau - \tau_N = 0 \tag{8}$$

To achieve (8), we apply back-propagation learning algorithm based on the gradient

$$\Delta w(t) = -\eta \frac{\partial E}{\partial w} \tag{9}$$

where η is the learning rate.

The objective function for a single output case is to minimize the error defined in (8) as

$$E = \frac{1}{2}\tau_C^2 \tag{10}$$

We need to calculate the gradient. Differentiating (10) yields the gradient as

$$\frac{\partial E}{\partial w} = -\tau_C \frac{\partial \tau_N}{\partial w} \tag{11}$$

where the term $\frac{\partial \tau_N}{\partial w}$ is available and can be obtained.

Therefore, weights are updated as

$$w(t+1) = w(t) + \eta\tau_C \frac{\partial \tau_N}{\partial w} \tag{12}$$

3.2. Reference Compensation Technique

The RCT scheme shown in Fig. 4 is quite different from the FEL in that compensation is done at the trajectory level not in the control output level[12,13]. The control objective of the neural network is same as to minimize the output errors. The output of the neural network is added to the input trajectory so that the error becomes

$$e = x_d - x + x_N \tag{13}$$

where x_d is the desired input and x_N is the output from neural network. The error contributes to the controller output as

$$\begin{aligned} \tau &= Kx_N + Ke \\ &= \tau_N + \tau_C \end{aligned} \tag{14}$$

which is same as (6). Here the format of τ_C can be various depending upon what kinds of controllers are used for the system. The case of equation (14) is when the proportional controller is used only for simplicity.

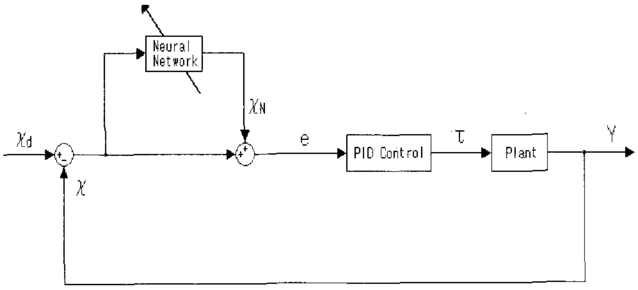

Figure 4. RCT control scheme

Next is to develop the learning algorithm to generate x_N for the RCT scheme to minimize the errors. The same objective function in (10) is used. To calculate the gradient in (4), differentiating (10) yields the gradient as

$$\frac{\partial E}{\partial w} = -\tau_C K \frac{\partial x_N}{\partial w} \tag{15}$$

Therefore, the difference from the FEL is the multiplication of the controller gain K so that the learning rate is relatively selected as small values.

4. Inverted pendulum control application

4.1 PID Control Scheme

The PID controller is still dominant in the industries since the method is efficient and easy to implement. Here the PID controller is used for the nonlinear system control. The positional error and the angle error of the inverted pendulum system are defined as

$$e_\theta = \theta_d - \theta, \quad e_x = x_d - x \tag{16}$$

Control inputs of the PID controller are defined as

$$u_\theta = k_{p\theta}e_\theta + k_{d\theta}\dot{e}_\theta + k_{i\theta}\int e_\theta dt \tag{17}$$

$$u_x = k_{px}e_x + k_{dx}\dot{e}_x + k_{ix}\int e_x dt \tag{18}$$

The total control input for one axis is the sum of (17) and (18).

$$\tau_C = u_\theta + u_x \tag{19}$$

4.2 FEL Control Scheme

The FEL scheme adds the neural network compensating signal to the equation (19).

$$\tau = \tau_C + \tau_N \tag{20}$$

where τ_N is the output from neural network. The learning algorithm is same as shown in the previous section.

4.3 RCT Control Scheme

The RCT scheme is quite different from the FEL scheme. The structure of neural network is shown in Fig. 5. The two layered feed-forward structure is used. Inputs are a combination of position and angle errors and desired position and angle values. For the experiment, 9 hidden units are used.

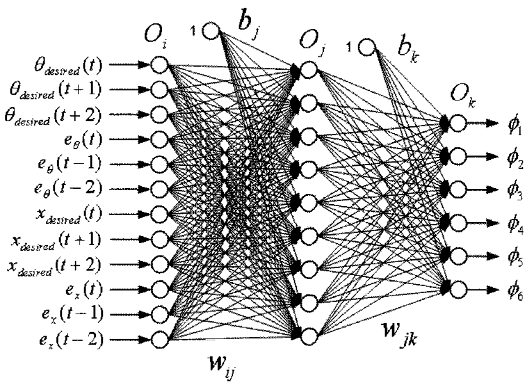

Figure 5. Neural network structure for the RCT

The PID controller with compensating signals from neural network forms the control inputs as

$$u_\theta = k_{p\theta}(e_\theta + \phi_1) + k_{d\theta}(\dot{e}_\theta + \phi_2) + k_{i\theta}(\int e_\theta dt + \phi_3) \tag{21}$$

$$u_x = k_{px}(e_x + \phi_4) + k_{dx}(\dot{e}_x + \phi_5) + k_{ix}(\int e_x dt + \phi_5) \tag{22}$$

Define the neural network output as

$$\Phi = \Phi_\theta + \Phi_x \tag{23}$$

where $\Phi_\theta = k_{p\theta}\phi_1 + k_{d\theta}\phi_2 + k_{i\theta}\phi_3$

$\Phi_x = k_{px}\phi_4 + k_{dx}\phi_5 + k_{ix}\phi_6$

From (21), (22), and (23), we have

$$k_{p\theta}e_\theta + k_{d\theta}\dot{e}_\theta + k_{i\theta}\int e_\theta dt + k_{px}e_x + k_{dx}\dot{e}_x + k_{ix}\int e_x dt$$
$$= \tau - \Phi \tag{24}$$

Define the training signal v as the PID controller outputs.

$$v = k_{p\theta}e_\theta + k_{d\theta}\dot{e}_\theta + k_{i\theta}\int e_\theta dt + k_{px}e_x + k_{dx}\dot{e}_x + k_{ix}\int e_x dt \tag{25}$$

The objective function to be minimized is defined as

$$E = \frac{1}{2}v^2 \tag{26}$$

Differentiating (26) yields the gradient as

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial v}\frac{\partial v}{\partial w} = v\frac{\partial v}{\partial w} = -v\frac{\partial \Phi}{\partial w} = -v\left(\frac{\partial \Phi_\theta}{\partial w} + \frac{\partial \Phi_x}{\partial w}\right) \tag{27}$$

where

$$\frac{\partial \Phi_\theta}{\partial w} = k_{p\theta}\frac{\partial \phi_1}{\partial w} + k_{d\theta}\frac{\partial \phi_2}{\partial w} + k_{i\theta}\frac{\partial \phi_3}{\partial w}$$

$$\frac{\partial \Phi_x}{\partial w} = k_{px}\frac{\partial \phi_4}{\partial w} + k_{dx}\frac{\partial \phi_5}{\partial w} + k_{ix}\frac{\partial \phi_6}{\partial w}$$

5. Experiments

5.1 Experimental setups

Fig. 6 shows the experimental setups for the inverted pendulum system kit. The kit consists of inverted pendulum, control hardware and a motor.

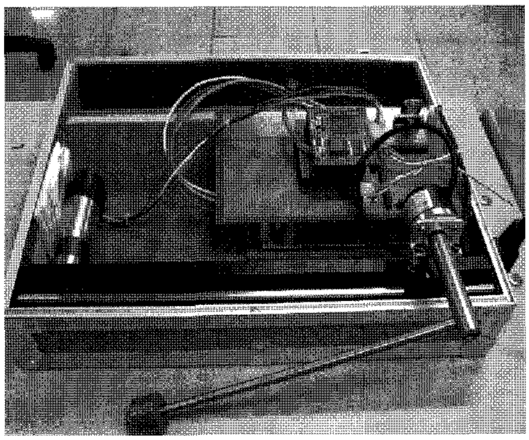

Figure 6. Experimental setup

Hardware is composed of a DSP board and an FPGA as shown in Fig. 7. The DSP board is used for neural network control and the FPGA chip is used for the encoder counter.

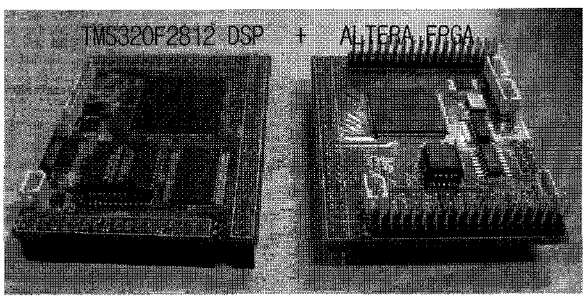

Figure 7. DSP and FPGA

5.2 User GUI

A user can test different neural network control schemes by selecting menus in the control panel shown in Fig. 8. Results can be displayed interactively. The PID controller gains can be changed with ease.

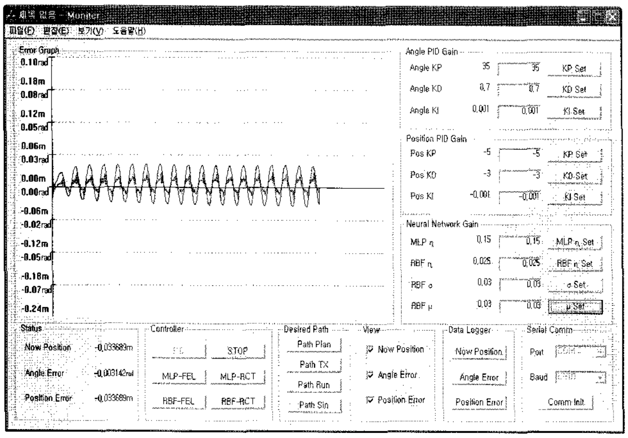

Figure 8 User GUI program

Fig. 9 shows how to set the desired path. A user can draw the path by dragging a mouse, then the desired path is automatically designed.

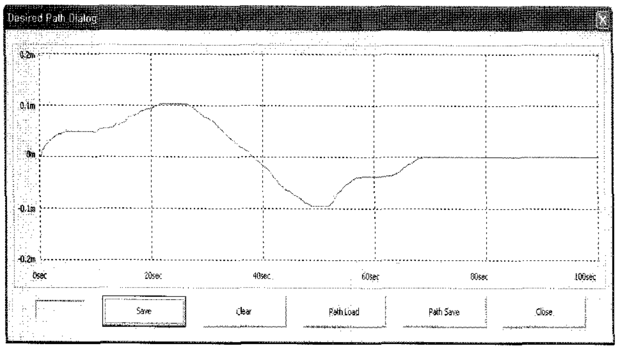

Figure 9 Set the desired path

5.3 Experimental results

(1) PID control

Several experiments are conducted with the kit. First of all, the PID controller is tested. Among many experiments, the best performance is selected and plotted in Fig. 10. As expected, we found that balancing and tracking control at the same time by the PID controller is quite difficult. Although the stable response is obtained, the oscillating behavior is observed.

(2) FEL scheme

Fig. 11 shows the results of the FEL scheme with the MLP network. The performance is much better than that of the PID controller. When the RBF network is used with the FEL scheme, the performance is compatible as shown in Fig. 12.

(3) RCT scheme

Fig. 13 and 14 show the results by the RCT scheme with MLP and RBF network, respectively. The performance is compatible with those of the FEL case. Performances of each controller can be easily compared with the GUI program. All of neural network control schemes successfully maintain the balance and track the desired position.

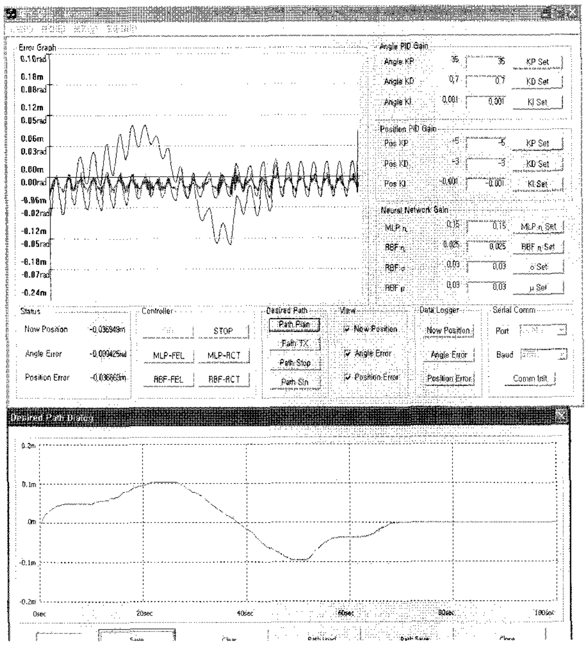

Figure 10 Result of PID controller

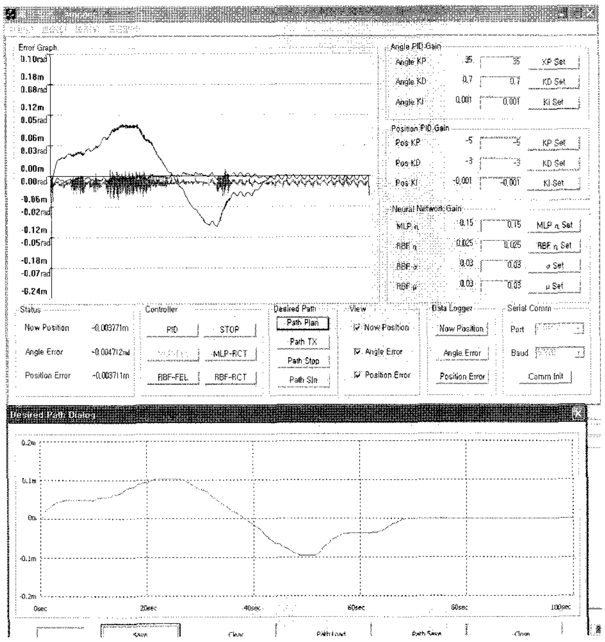

Figure 11 Result of MLP-FEL scheme

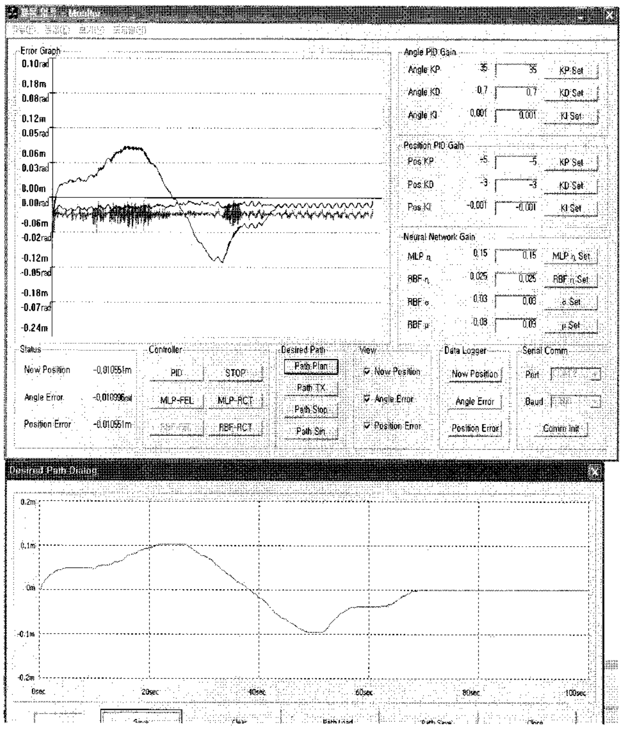

Figure 12 Result of RBF-FEL scheme

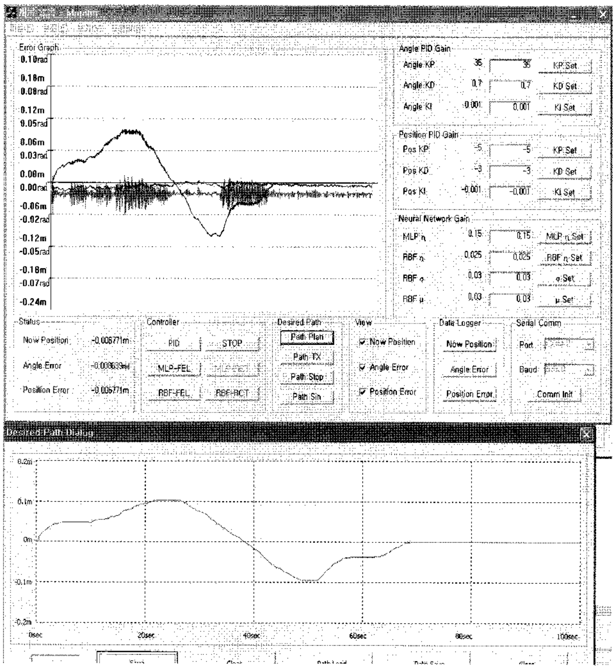

Figure 13 Result of MLP-RCT scheme

6. Conclusion

The intelligent control education kit is developed to test intelligent control algorithms. Although the kit is required to include many functions, minimum functions are developed at the current stage. Neural network control algorithms such as the FEL scheme and the RCT scheme are tested with ease. Results can be plotted easily and compared with those of PID controllers. Performances of neural network control schemes are better than that of the PID controller. Among different neural network control schemes, performances are compatible.

A complete educational kit is an on-going project and extensions to control other systems such as a mobile pendulum or mobile robots and to include fuzzy control algorithms are considered.

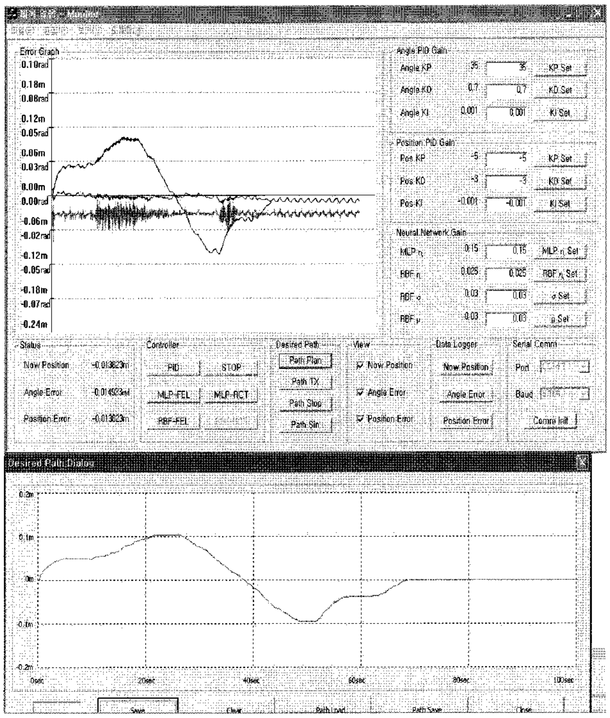

Figure 14 Result of RBF-RCT scheme

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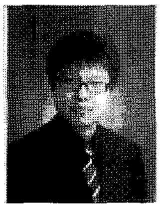

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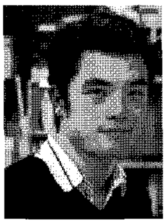

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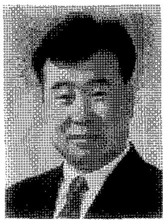

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