# A Robust PID Control Method with Neural Network

**Seong-Ho Kang, Yong-Gu Lee** and **Ki-Hwan Eom,** *Member, KIMICS*

***Abstract***—The problem of reducing the effect of an unknown disturbance on a dynamical system is one of the most fundamental issues in control design. We propose a robust PID (Proportional Integral Derivative) control method with neural network for improving the performance due to the rejection of an unknown disturbance. The proposed system consists of a model of the plant, a conventional PID controller and a multi-layer neural network, and is composed of two loop; the first loop enables the system to achieve stability of system, the second loop rejects an unknown disturbance. Simulation and experiment results show that the proposed method improves considerably on the performance of the conventional PID control method and the typical IMC method using neural network.

***Index Terms***—Robust control, multilayer neural network, PID control.

## I. INTRODUCTION

Most industrial processes are controlled using PID controller. The popularity PID controllers can be attributed partly to their robust performance in a wide range of operating conditions and partly to their functional simplicity, which allows process engineers to operate them in a simple and straightforward manner. Although the PID algorithm itself is essentially simple, commercial implementations of PID controllers contain a multitude of additional features that embody the experience of many years of application [1].

The IMC (Internal Model Control) continue to be a powerful strategy in industrial processes control application. This structure provides a practical tool to influence dynamic performance and robustness to modelling errors transparently in the design [2].

In process control applications, a neural network can be incorporated with the controllers in either direct or indirect methods. In the direct method, a neural network is trained with observed data from the system to represent its inverse dynamics. In the indirect method the neural network is trained with input-output data from the dynamic system to represent the forward dynamics [3].

The problem of reducing the effect of an unknown disturbance on a dynamical system is an important in control design. And it is an important problem in designing a PID controller to achieve a specified performance and robust stability, since PID controllers are widely used in industrial processes with time delay or other uncertainties [4]. In this case, the optimum problem is generally dealt with using some well-known optimization methods, e.g., [7], mixed [8] and semidefinite programming approaches [9].

In order to improve on the performance of the PID control method, we propose a robust PID control method using the neural network. The proposed method comprises of two loop; the first loop has the IMC structure and enables the system to achieve stability of system, and the second loop has the neural network filter and rejects an unknown disturbance.

In order to verify the efficiency of the proposed method, and to compare it with the conventional PID control method and the typical IMC method using neural network, we perform simulation and experiment on the position control of DC servo motor.

## II. INTERNAL MODEL CONTROL METHOD

The IMC (Internal Model Control), first proposed in Morari and Zafiriou, has found a number of successful applications. Fig. 2-1 shows the block diagram of IMC system.

$P(s)$ is the transfer function of the process, $M(s)$ is an model of the process, $Q(s)$ is the controller. $Q(s)$ and $M(s)$ is usually referred to as the internal model. $D(s)$ is an unknown disturbance, and $N(s)$ is a noise [2][5].

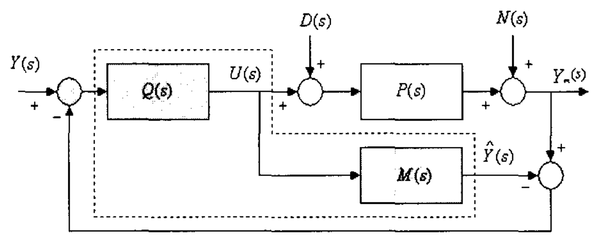


Fig. 2-1 IMC block diagram.

Fig. 2-1 can be rearranged to the form of Fig. 2-2 [5].

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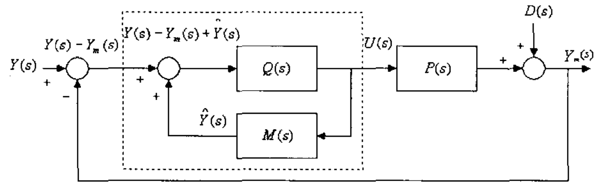


Fig. 2-2 Rearrangement of IMC structure.

In Fig. 2-2, is simply the error term used by a standard feedback controller. Therefore, The IMC structure can be rearranged to the feedback control structure.

## III. TYPICAL INTERNAL MODEL CONTROL METHOD USING NEURAL NETWORK

The IMC method incorporates the model of the plant and its corresponding inverse, which can be both designed by neural network. Then an IMC structure can be implemented in a straightforward way and leads to good closed loop performances when a perfect model of the plant is available. An IMC structure using Neural Networks (NN) is given in Fig. 3-1.

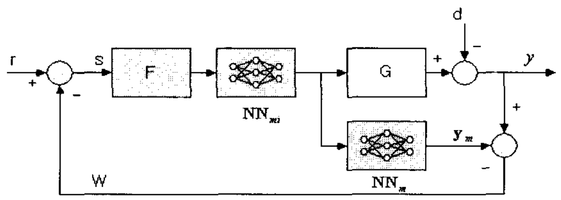


Fig. 3-1 Typical IMC method using neural network.

In Fig. 3-1, the neural model of the studied system is connected in parallel with the real plant . The difference between their output variables is used as an input to the neural controller. and denote the reference signal and input disturbance respectively, and denotes a filter [2].

## IV. PROPOSED METHOD

It is an important problem in designing a PID controller to achieve a specified robust performance and robust stability, since PID controllers are widely used in industrial processes with time delay or other uncertainties. We propose a robust PID control method with neural network, which allows the rejection of an unknown disturbance. The proposed system consists of a model of the plant, a conventional PID controller and a multi-layer neural network. Fig. 4-1 shows the structure of the proposed system.

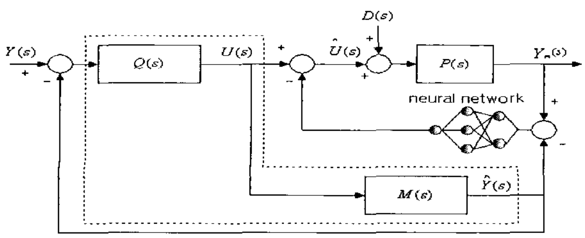


Fig. 4-1 Structure of the proposed system.

The feedback controller, $G_c(s)$, contains both the internal model, $M(s)$, and the internal PID controller, $Q(s)$. The feedback controller of a closed-loop system can be synthesized by equation (4.1).

$$G_c(s) = \frac{Q(s)}{1 + M(s)Q(s)} \tag{4.1}$$

In Fig. 4-1, $D(s)$ is an unknown disturbance affecting the system. The manipulated input $U(s)$ is introduced to both the process and its model. If the output of the neural network is $K(s)$, the output for the proposed system is given by equation (4.2).

$$Y_m(s) = [U(s) - K(s) + D(s)]P(s) \tag{4.2}$$

If $K(s) = D(s)$, the $Y_m(s)$ is equal to the optimal output $\hat{Y}(s)$, then the perfect set-point tracking and the disturbance rejection are achieved. Therefore the first loop enables the system to achieve the stability of system. The second loop rejects an unknown disturbance.

The back-propagation algorithm is used to train the multi-layer neural network. The algorithm adjusts the multi-layer neural network parameters in oder to minimize the mean square error:

$$e_p(t) = \frac{1}{2}(y_m(t) - \hat{y}(t))^2 \tag{4.3}$$

where $y_m(t)$ is an output of the process, $\hat{y}(t)$ is an output of the process model. The steepest descent algorithm for the approximate mean square error is

$$w_{ji}(t+1) = w_{ji}(t) - \alpha \frac{\partial e_p(t)}{\partial w_{ji}(t)} \tag{4.4}$$

$$w_{kj}(t+1) = w_{kj}(t) - \alpha \frac{\partial e_p(t)}{\partial w_{kj}(t)} \tag{4.5}$$

where $\alpha$ is the learning rate. $w_{ji}$ is the weight connecting a hidden neuron, $j$, and an output neuron, $i$. $w_{ji}$ is the weight connecting a hidden neuron, $j$, and an input neuron, $k$. By applying the chain rule, the change is

$$\frac{\partial e_p(t)}{\partial w_{ji}(t)} = \frac{\partial e_p(t)}{\partial \alpha_2(t)} \frac{\partial \alpha_2(t)}{\partial n_2(t)} \frac{\partial n_2(t)}{\partial w_{ji}(t)} \tag{4.6}$$

$$\frac{\partial e_p(t)}{\partial w_{ji}(t)} = \frac{\partial e_p(t)}{\partial \alpha_2(t)} \frac{\partial \alpha_2(t)}{\partial n_2(t)} \frac{\partial n_2(t)}{\partial w_{ji}(t)} \tag{4.7}$$

$$\frac{\partial e_p(t)}{\partial w_{kj}(t)} = \frac{\partial e_p(t)}{\partial \alpha_2(t)} \frac{\partial \alpha_2(t)}{\partial n_2(t)} \frac{\partial n_2(t)}{\partial \alpha_1(t)} \frac{\partial \alpha_1(t)}{\partial n_1(t)} \frac{\partial n_1(t)}{\partial w_{kj}(t)} \tag{4.8}$$

where $a_2(t)$ and $a_1(t)$ is the sigmoid function. $n_2(t)$ and $n_1(t)$ is given by (4.9).

$$\alpha_2(t)=\frac{1}{1+e^{-n_2(t)}},\ \alpha_1(t)=\frac{1}{1+e^{-n_1(t)}} \quad (4.9)$$

$$n_2(t)=\sum w_{ji}(t)\cdot\alpha_1(t),\ n_1(t)=\sum w_{kj}(t)\cdot\alpha_0(t) \quad (4.10)$$

Where $a_0(t)$ is the input of the neural network.

## V. SIMULATION

In this section, we present some simulation examples to demonstrate the effect of the proposed method. Dynamic equation of DC servo motor is

$$\frac{T}{K_t}\ddot{\theta}(t)+\frac{1}{K}\dot{\theta}(t)=V \quad (5.1)$$

where $\theta$ is the angle, $\dot{\theta}(t)$ is the angle velocity, $\ddot{\theta}(t)$ is the angle acceleration of DC servo motor, and $V$ is the input voltage of the DC servo motor respectively. Here constant $T$ of system and coefficient $K_t$ are given by equation (5.2).

$$T=\frac{JR}{K_bK_m+Rf}$$
$$K_t=\frac{K_m}{K_bk_m+Rf} \quad (5.2)$$

The inertia moment $J$ is $28\times10^{-6}[kgm^2]$, the coil resistance $R$ is $5.5[\Omega]$, the inverse electromotive force $K_b$ is $67\times10^{-3}[kgm^2]$, the toque constant $K_m$ is $68\times10^{-3}[Vsrad^{-1}]$ and the friction coefficient $f$ is $10\times10^{-3}[Nm]$ respectively. Integral algorithm is Runge-Kutta fourth order algorithm and step-size is $5[m\text{sec}]$ through simulation.

We will discuss a conventional PID controller, an typical IMC method using neural network and the proposed method. Neural network in the proposed method is constructed with 4 neuron of input layer, 10 neuron of hidden layer and a neuron of output layer respectively. Neural network parameters are that input is difference between the practical plant and a model of the plant, the initial value of the weight and the bias is random value among [-0.1, 0.1] and the learning rate has 0.02. The reference output and the disturbance are given by equation (5.3).

$$y_d(t)=u(t)$$
$$d(t)=0.2\sin(2t) \quad (5.3)$$

The PID controller parameters are $K_p=2, K_d=10, K_i=0.06$. Learning iteration of neural network is 900. Neural network parameters in the typical IMC method using neural network is the same as the proposed method. Fig. 5-1, Fig. 5-2 is the response and the error curve of conventional PID control method respectively.

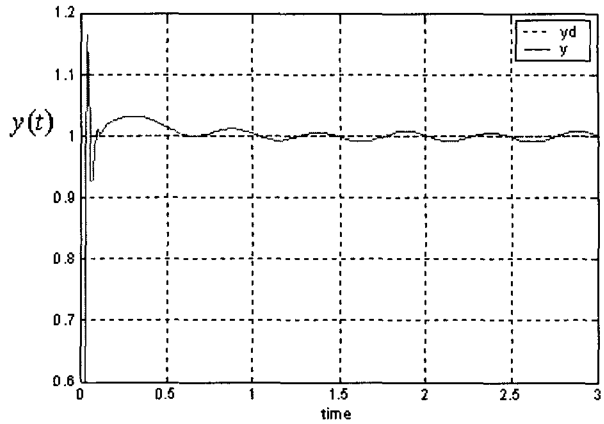


Fig. 5-1 The response curve of the conventional PID control method.

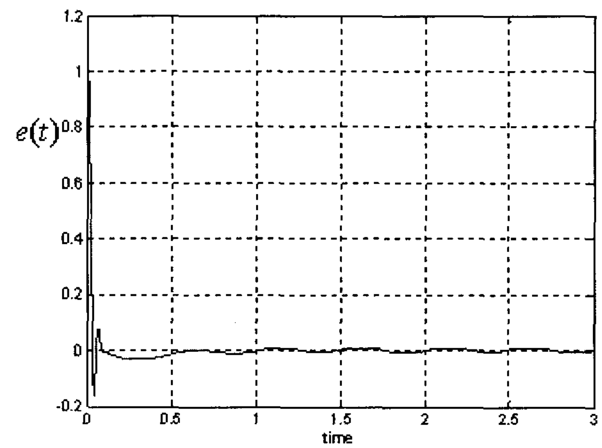


Fig. 5-2 The error curve of the conventional PID control method.

Fig. 5-3, Fig. 5-4 is the response and the error curve of the typical IMC method using neural network respectively.

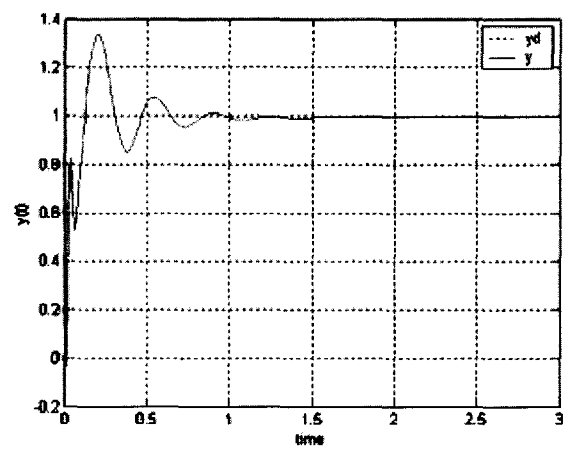


Fig. 5-3 The response curve of the typical IMC method using neural network.

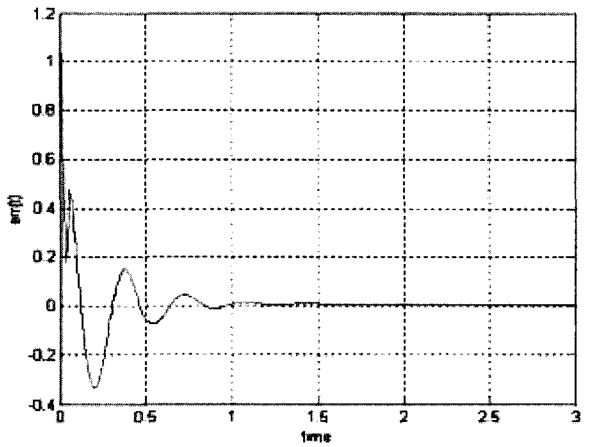


Fig. 5-4 The error curve of the typical IMC method using neural network.

Fig. 5-5, Fig. 5-6 is the response and the error curve of the proposed method respectively.

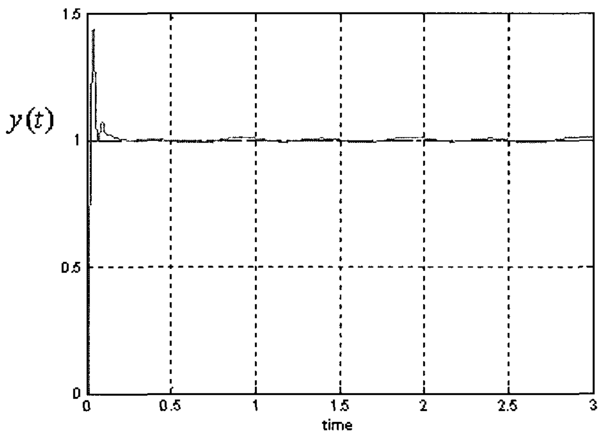


Fig. 5-5 The response curve of the proposed method.

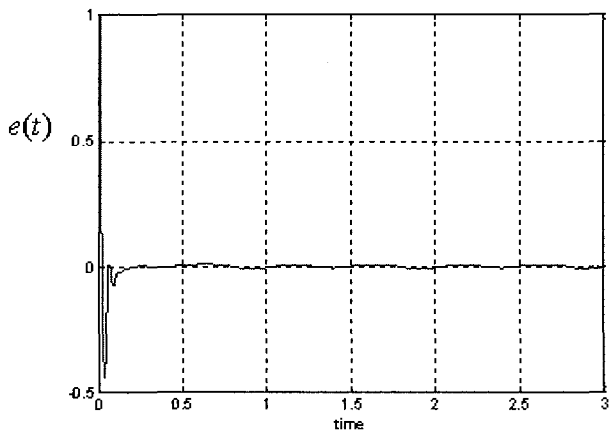


Fig. 5-6 The error curve of the proposed method.

Through simulation, the conventional PID control method has resulted oscillating remain error that was effected by disturbance. The typical IMC method using neural network has resulted nearly zero of remain error but settling time was long. The proposed method has resulted nearly zero of remain error and settling time was short.

## VI. EXPERIMENT

Fig. 6-1 shows the MM-LDM (Moving Magnetic Linear DC Motor) that was used with the plant of the experiment.

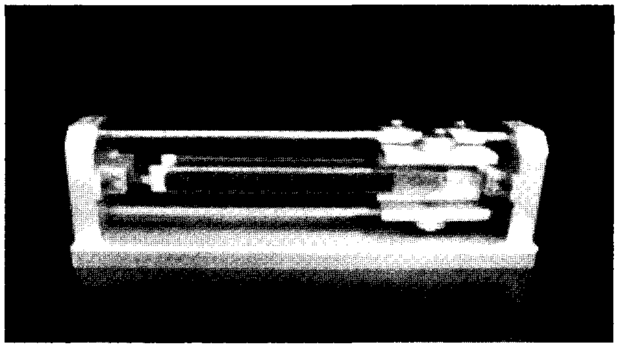

Fig. 6-1 The MM-LDM.

Table 6.1 is the main specification of the MM-LDM

Table 6.1. A main specification of MM-LDM.

| | |
|---|---|
| voltage source V | 12 V |
| thrust F | 1 N |
| speed V | 1.2 m/s |
| magnetic flux density B | 0.26 Wb/m$^2$ |
| An activate distance X | 0.1 m |
| Mass of needle M | 0.32 kg |
| counter electromotive force constant Ke | 1.5 Vs/m |
| thrust constant Kf | 0.153 kgf/A |

The output of the MM-LDM is

$$\mathrm{F} = N_l l B I = k_f I \quad \text{(N)} \qquad (6.1)$$

where, parameters are $N_l$ = magnetic flux number, $l$ = permanent magnet width, $B$ = permanent magnet flux density and $I$ = current. Velocity $S$ of actuator is

$$S = \frac{V - RI}{N_l l B} \qquad (6.2)$$

where $R$ is resistance of electromagnet. the state equation of the MM-LDM is

$$\begin{bmatrix} \dot{X} \\ \ddot{X}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -1/T \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} + \begin{bmatrix} 0 \\ K_m/T \end{bmatrix} V \qquad (6.3)$$

where $\dot{X}_1$ is the velocity and $\dot{X}_2$ is the acceleration of the MM-LDM respectively, $T$ and $K_m$ is following

$$T = \frac{RM}{K_e K_f}, \; K = \frac{1}{K_e} \qquad (6.4)$$

Fig. 6-2, Fig. 6-3 is the block diagram of the experiment device and the photograph of experimental device respectively.

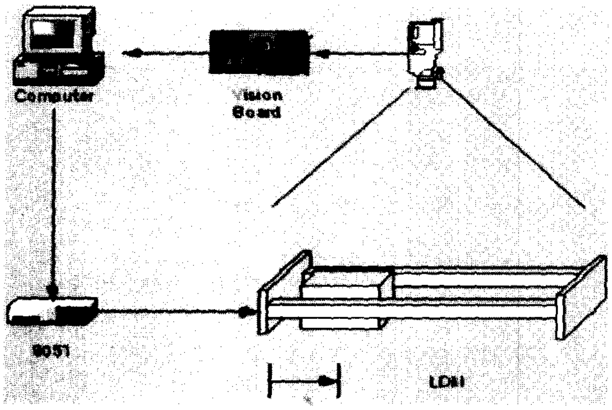


Fig. 6-2 The block diagram of the experiment device

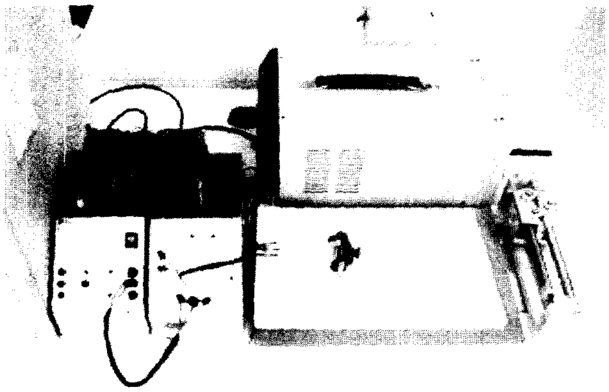

Fig. 6-3 The photograph of the experimental device

The PID controller and the neural network were operated by the main computer. The output value of the controller was transferred by RS-232 protocol into the MM-LDM actuator that was constructed with the 8051 microprocessor.

The CCD camera was used with position sensor. Vision systems are increasingly being applied to a wide range of manufacturing problems, for example, in inspection, assembly and robot and vehicle guidance. Image processing techniques are used to give information about the presence of targets, their dimensions, and also the presence or absence of features [6]. We used image grabber of 30 frames/s.

The parameters of the neural network in experiment were that the learning rate is 0.02, the neuron of the input layer is 4, the neuron of the hidden layer is 10, the neuron of the output layer is 1, the initial weight and the bias are the random value between [-0.1 0.1]. The reference input and the disturbance were given by equation(6.5).

$$y_d(t)\begin{cases}90 & 0 \le t < 3\\ 30 & 3 \le t < 6\\ 60 & 6 \le t < 9\end{cases} \qquad (6.5)$$

$$d(t) = 5\sin(6\pi t)$$

Initial position and velocity of MM-LDM have fixed with zero. PID parameters were fixed with $K_p = 27, K_d = 10, K_i = 0.001$. Learning iteration of neural network was 5000. Fig. 6-4, Fig. 6-5 is the response curve of the conventional PID control method and the typical IMC method using neural network respectively.

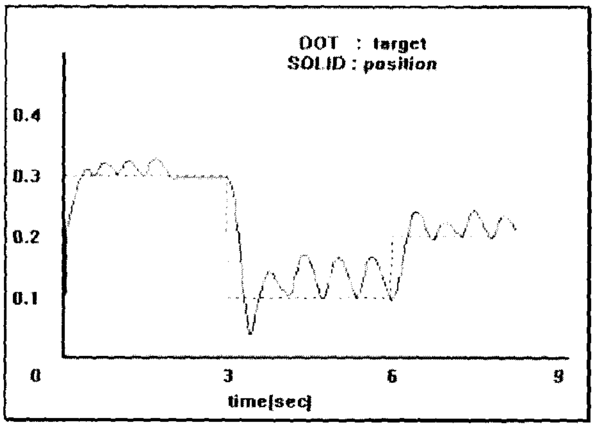


Fig. 6-4 The response curve of the conventional PID control method

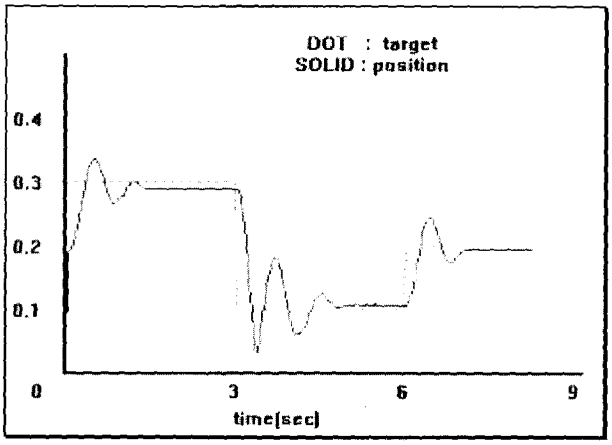


Fig. 6-5 The response curve of the typical IMC method using neural network

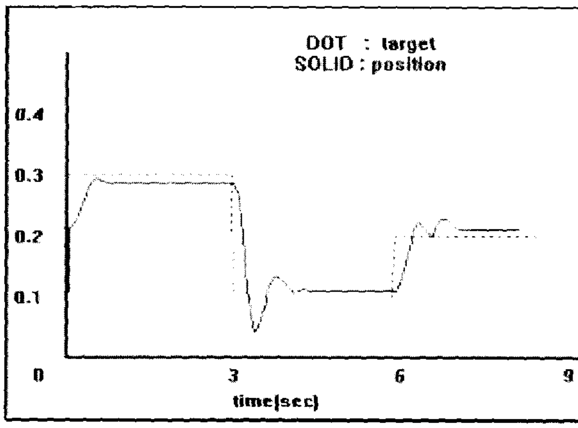


Fig. 6-6 The response curve of the proposed method.

Fig. 6-6 is the response curve of the proposed method.

Through experiment, the conventional PID control method has resulted oscillation that was effected by the disturbance. The typical IMC method using neural network has resulted robust for the disturbance, but settling time was long and overshoot was large. The proposed method has resulted robust for disturbance, settling time was short and overshoot was small.

## VII. CONCLUSION

The problem of reducing the effect of an unknown disturbance on a dynamical system is one of the most fundamental issues in control design. In order to resolve this problem, we proposed a robust PID control method with neural network. The proposed system consists of a model of the plant, a conventional PID controller and a multi-layer neural network. The control structure used IMC, and the BP algorithm was employed as a learning algorithm to train the neural network. The proposed system was composed of two loop; the first loop enables the system to achieve stability of system, the second loop rejects an unknown disturbance.

In order to verify the effectiveness of the proposed method, and to compare it with the conventional PID control method and the typical IMC method using neural network, we simulated and experimented on the position control of DC servor motor. From results of the simulation and the experiment, the proposed method has resulted robust for disturbance, settling time was short, and overshoot was small.

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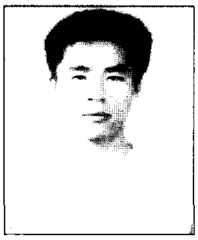

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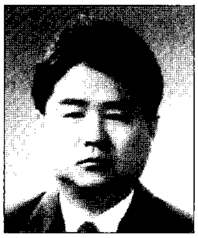

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