PID Controllers Using Neural Network For Multi-Input Multi-Output Magnetic Levitation System

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Abstract--*This paper deals with a design scheme for PID controllers with neural network (NN) for multi-input multi-output (MIMO) magnetic levitation systems. PID controllers are considerably used in industrial processes because their simple structure that consists of only three parameters. Sofar, considerable attention has been given to the use of SISO procedures for the tuning of decentralized PID controllers for MIMO systems. This approach suffers from the need for full model knowledge of the plant to compute the ultimate point, and it finally uses only this information to design the controller. Here, we develop a controller without requirements of the full model knowledge of the plant. We develop a NN that can be used to assist PID controllers for MIMO systems. The NN is used to compensate for inputs-outputs coupling of the MIMO system and to stabilize the PID controllers. Finally, the effectiveness of the proposed controller is confirm through experimental studies.*

Keywords: NN, MIMO, PID

A. Introduction

PID controllers are considerably used in industrial processes, because their simple structure that consists of only three parameters[1],[2]. So far, considerable attention has been given to the use of single-input single-output (SISO) procedures for the tuning of decentralized PID controllers for multi-input multi-output (MIMO) systems. This approach suffers from the need for full model knowledge of the plant to compute the ultimate point, and it finally uses only this information to design the controller [2], [3], [4], [5]. The drawback of such design procedure is that it may be fairly time consuming and that it requires personnel with high skill in modeling, system identification and controller design. More over if the plant is unknown and complex, this procedure may be unsatisfactory.

The use of a neural network (NN) in the control system appears to offer new and promising developments toward better performance and can solve several problems in control systems. For example, the NN is suitable for use in complex systems, non linear systems, systems with disturbances, unknown systems, dynamical systems, systems with uncertainties and model mismatch [6], [7], [8]. Therefore, many controller methods using NN have been proposed. The use of the NN to tune the gains of the PID has been proposed in [9], [10].

The effectiveness of the used of NN with a PID controller for controlling the SISO system is proved in our previous paper [11]. In this paper, we will develop an NN that can be used to assist PID controllers for controlling MIMO systems. The NN is used to compensate for inputs-outputs coupling of the MIMO system and to stabilize the PID controllers. We will develop a controller without requirements of the full model knowledge of the plant.

On the other hand, magnetic levitation systems are extensively used in various applications, such as frictionless bearings, high-speed maglev passenger trains, levitation of wind tunnel models, and vibration isolation tables. Because of open-

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loop instability and inherent nonlinearities associated with electromechanical dynamics, controlling this kind of system is usually a challenging problem [12], [13], [14], [15]. The performance of the proposed control strategy is then demonstrated through experimental studies on a magnetic levitation system.

B. PID Controllers Using NN

To implement PID controllers on a computer, it must be converted intoa digital form. A common way of doing this is to discretize the controllers. The proportional part of the controller is discretized straightforwardly by replacing continuous variables with their sampled versions. We can then express discrete-time PID controllers as

$$u_{PID,1}(k) = \frac{K_{p,1}e(k) + K_{i,1}T_s\sum_{0}^{k} e(k) + K_{d,1}\{e_1(k) - e_1(k-1)\}}{T_s} \quad (1)$$

$$u_{PID,2}(k) = \frac{K_{p,2}e(k) + K_{i,2}T_s\sum_{0}^{k} e(k) + K_{d,2}\{e_2(k) - e_2(k-1)\}}{T_s} \quad (2)$$

where $u_{PID,1}$, $u_{PID,2}$ are the outputs of the PID controller, $K_{p,1}, K_{p,2}$ are the proportional gains, $K_{i,1}, K_{i,2}$ are the integral gains, $K_{d,1}, K_{d,2}$ are the derivative gains, e_1 , e_2 are the errors and T_s , is the sampling time. Figure 1 shows the proposed controller structure. The controller out puts are given by:

$$u_{p,1}(k) = u_{PID,1}(k) + u_{NN,1}(k) \quad (3)$$

$$u_{p,2}(k) = u_{PID,2}(k) + u_{NN,2}(k) \quad (4)$$

where $u_{p,1}$, $u_{p,2}$ are the inputs of the plant, $u_{PID,1}$, $u_{PID,2}$ are the outputs of the NN and $u_{NN,1}$, $u_{NN,2}$ are the outputs of the NN.

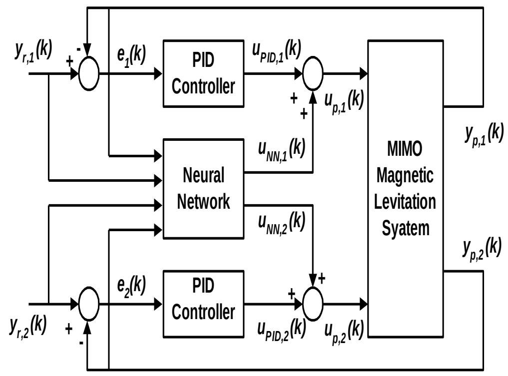

Figure 1. The structure of the proposed controller

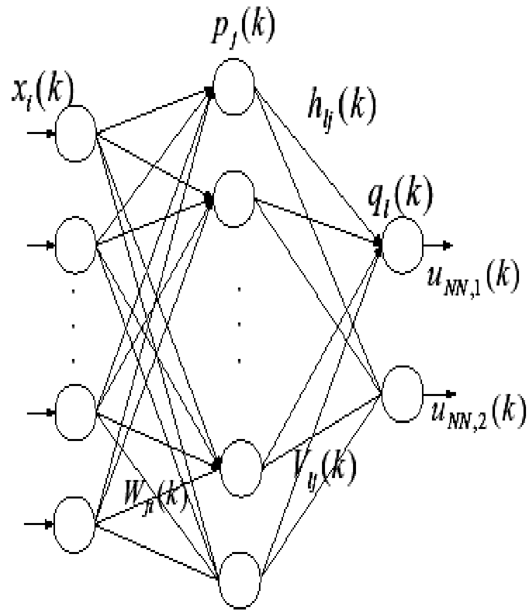

Figure 2.The structure of the NN

The structure of the NN

The structure of the NN is shown in Figure 2. Let $x_i(k)$ be the input to the *i*th node in the input layer, $p_j(k)$ be the input to the *j*th node in the hidden layer, $h_j(k)$ be the output of the *j*th node in the hidden layer, $q_i(k)$ be the input to the node in the output layer, and $u_{NN,i}(k)$ be the output of the node in the output layer.

Then, the relationships between the input layer and the output layer can be expressed as

$$
\begin{aligned}
p_j(k) &= \sum_i W_{ji}(k)x_i(k) && (5)\\
h_j(k) &= f(p_j(k)) && (6)\\
q_l(k) &= \sum_j V_j(k)h_j && (7)\\
u_{NN,l}(k) &= f(q_l(k)) && (8)
\end{aligned}
$$

where f (.) is the activation function. The sigmoid function for the activation function is

$$f(x) = \frac{2a}{1+\exp(-\mu x)} - a \qquad (9)$$

where $\mu > 0$, and a is a specified constant such that $a > 0$, and $f(x)$ satisfies $-a < f(x) < a$.The derivative of Eq.(9) can be written as

$$f'(x) = \frac{\mu}{2a}(a - f(x))(a + f(x)) \qquad (10)$$

Learning of the NN

The aim of NN training is to minimize the sum of the square of the error energy function.

$$E(k) = \frac{1}{2}\left[y_{r,l}(k) - y_{p,l}(k)\right]^2 \qquad (11)$$

The weights in the output and the hidden layers are updated using

$$
\begin{aligned}
V_{lj}(k) &= V_{lj}(k-1) + \eta\left(-\frac{\partial E(k)}{\partial V_{lj}(k)}\right) && (12)\\
W_{ji}(k) &= W_{ji}(k-1) + \eta\left(-\frac{\partial E(k)}{\partial W_{ji}(k)}\right) && (13)
\end{aligned}
$$

where η is the learning rate, and $\dfrac{\partial E(k)}{\partial V_{i,j}(k)}$ and $\dfrac{\partial E(k)}{\partial W_{i,j}(k)}$ can be obtained as

where

$$
\begin{aligned}
\frac{\partial E(k)}{\partial V_{lj}(k)} &= \frac{\partial E(k)}{\partial y_{p,l}(k)} \cdot \frac{\partial y_{p,l}(k)}{\partial u_{p,l}(k)} \cdot \frac{\partial u_{p,l}(k)}{\partial u_{NN,l}(k)} \cdot \frac{\partial u_{NN,l}(k)}{\partial q_l(k)}\\
&\quad \cdot \frac{\partial q_l(k)}{\partial V_j(k)}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial E(k)}{\partial W_{ji}(k)} &= \frac{\partial E(k)}{\partial y_{p,l}(k)} \cdot \frac{\partial y_{p,l}(k)}{\partial u_{p,l}(k)} \cdot \frac{\partial u_{p,l}(k)}{\partial u_{NN,l}(k)} \cdot \frac{\partial u_{NN,l}(k)}{\partial q_l(k)}\\
&\quad \cdot \frac{\partial q_l(k)}{\partial h_j(k)} \cdot \frac{\partial h_j(k)}{\partial p_j(k)} \cdot \frac{\partial p_j(k)}{\partial W_{ji}(k)}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial E(k)}{\partial y_{p,l}(k)} &= -(y_{r,l}(k) - y_{p,l}(k))\\
\frac{\partial y_{p,l}(k)}{\partial u_{p,l}(k)} &= J_{p,l}(k)\\
\frac{\partial u_{p,l}(k)}{\partial u_{NN,l}(k)} &= 1, \quad \frac{\partial q_l(k)}{\partial V_j(k)} = h_j(k)\\
\frac{\partial q_l(k)}{\partial h_j(k)} &= V_j(k), \quad \frac{\partial p_j(k)}{\partial W_{ji}(k)} = x_i(k)\\
\frac{\partial u_{NN,l}(k)}{\partial q_l(k)} &= \frac{\mu}{2a}(a - u_{NN,l}(k))(a + u_{NN,l}(k))\\
\frac{\partial h_j(k)}{\partial p_j(k)} &= \frac{\mu}{2a}(a - h_j(k))(a + h_j(k))
\end{aligned}
$$

Furthermore $J_{p,l}$ represents the Jacobian of the plant. In this study, we utilize the same method as in[16]:

$$J_{p,l}(k) = sgn\left(\frac{\partial y_{p,l}(k)}{\partial u_{p,l}(k)}\right) \qquad (14)$$

where *sgn (.)* is the sign function.

C. Experimental Studies

Setup and Parameters Design

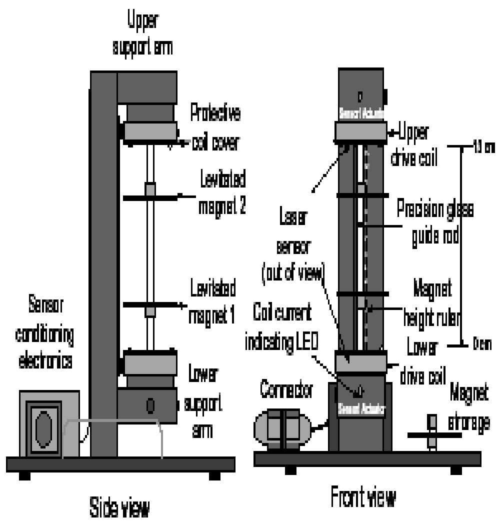

Figure3. Schematic diagram of the magnetic levitation system

The setup for this experiment is shown in Fig. 4. The computer system is used to run the education control product (ECP), to execute the program, and to communicate with the ECPs digital signal processing (DSP) based realtime controller. The realtime controller unit contains the DSP, servo/actuator interfaces, the servo amplifier and auxiliary power supplies. Four 16 bit analog to digital converters (ADCs) are used to digitize the laser sensor signals. Two optional auxiliary digital to analog converters (DACs) provide for realtime analog signal measurement [17].

Figure 4.Experimental setup

The magnetic levitation height (the plant output) is controlled using the voltage of the lower coil (the plant input) of the magnetic levitation system (the plant).

The system is tested using the proposed control strategy and compared with the conventional PID controller. To make fair comparison, we use the same reference signal and the same sampling time for all the controllers. All of the experiments are implemented at a sampling time (T_S) of 5.304 ms.

The inputs of NN were $X = [x1, x2, x3, x4]^T$ Other setting parameters for neural network were given in Table 1 where i is the number of neurons in the input layer, j is the number of neurons in the hidden layer, q is the number of neurons in the output layer, a and μ are the sigmoid constant and η is the learning rate. More over, all the network weights were initialized to small random values between [0;0.1].

Table 1. Parameters of The NN

i	j	l	a	μ	η
4	3	2	6.7	0.05	0.1

The result of using the conventional PID controllers is shown in Fig.5 where the dotted line shows the desired outputs and the solid lines hows the system outputs. Figure 6 shows the result when the gains of the PID controllers were set to 0.5, 0.5 and 0.07 for the proportional, the integral and the derivative gains, respectively. The result obtained using the proposed control strategy is shown in Fig. 6 with the same parameter as the PID controllers in Fig. 5. The system responses shows well tracking. If we compare the results of the conventional PID in Fig. 5 and the proposed control strategy in Fig. 6, it can be said that the proposed control strategy gives a better performance than using the conventional PID controllers.

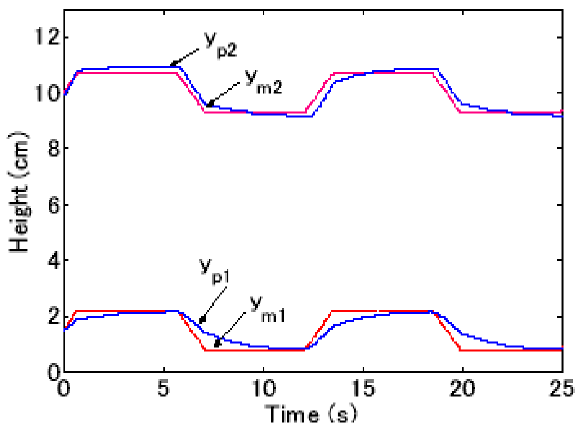

Figure 5. System outputs of the PID controller with the gains: $K_{P,1} = K_{P,2} = 0.5$, $K_{I,1} = K_{I,2} = 0.5$ and $K_{D,1} = K_{D,2} = 0.07$

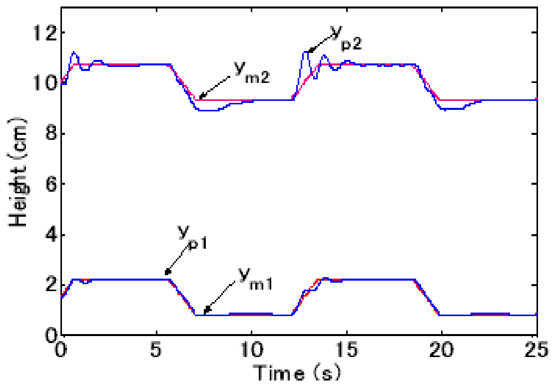

Figure 6. System outputs of the proposed method with the same param eters as the PID controller in Fig. 5

D. Conclusion

In this paper, an NN is utilized to compensate for inputs- outputs coupling of the MIMO system and to stabilize the PID controllers. We developed the controller without requirements the knowledge of the plant. The experimental results showed the effectiveness of the proposed controller for controlling MIMO magnetic levitation system.

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