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Neural Network Compensation Technique for Standard PD-Like Fuzzy Controlled Nonlinear Systems

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Abstract

In this paper, a novel neural fuzzy control method is proposed to control nonlinear systems. A standard PD-like fuzzy controller is designed and used as a main controller for the system. Then a neural network controller is added to the reference trajectories to form a neural-fuzzy control structure and used to compensate for nonlinear effects. Two neural-fuzzy control schemes based on two well-known neural network control schemes, the feedback error learning scheme and the reference compensation technique scheme as well as the standard PD-like fuzzy control are studied. Those schemes are tested to control the angle and the position of the inverted pendulum and their performances are compared.

Key Words : Inverted pendulum, fuzzy logic controller, neural network controller, FEL, RCT

1. Introduction

Endowing intelligence to dynamical systems has been inspired by an endless desire of human beings to make a human-like system. Two main streams of intelligence are known as a fuzzy logic and a neural network system [1].

Fuzzy control has been known as a quite effective intelligent method for representing human expressions to a dynamical system [2,3]. Transforming linguistic values into numerical values, a system can be controlled by human intuition such as experience and expertise. Transfer of experiences and intuitions of a human operator is a critical factor to judge the system performance of obtaining the desired response of the dynamical system.

Since the performance of the fuzzy controller relies on the experience of the operator, a novice fuzzy control operator prefers to using a standard PD-like or a PI-like fuzzy controller [3,4]. Even though standard fuzzy controllers work well under a certain situation, in the most of cases, fuzzy rules are required to be modified and reformulated to get better results. However, designing fuzzy rules is neither easy nor systematic. Even the optimal fuzzy rules have been designed, the performance of the system is not guaranteed until the controller is robust enough to deal with system parameter variation and outer disturbances. So, the way of designing rules is considered as a burden that has to be intelligent [3]. This can be one of defects of the fuzzy control method.

To solve this problem, adaptive techniques have been introduced into the framework of a fuzzy controlled system structure. Designed fuzzy rules are adaptively adjusting according to changes in system parameters and disturbances [5]. The center and end values of the membership functions of fuzzy rules are adjusted to minimize the global errors. The neuro-fuzzy control structure has been proposed to mimic fuzzy control process by designing a multi-layered neural network structure. Each layer of a neural network is required to function each process of the fuzzy control such as fuzzification, inference, defuzzification, and so on [6-10].

The other aspect of improving performance of the fuzzy control is to use the compensation technique by introducing neural networks [11-16]. The well-known neural network compensation technique is the feedback-error learning (FEL) scheme. Applying the FEL scheme to a fuzzy controlled system improves the system performance by adding compensating signals at the control input level to achieve the inverse dynamics control.

In this paper, as an extension of our previous works [14-16], a novel neural network compensation technique for fuzzy controlled nonlinear systems is proposed. The proposed control technique is formed based on the conventional fuzzy control structure. The idea of the proposed scheme is that modifying inputs by a neural network compensator results in modifying the fuzzy rules. A neural network controller is added to the reference trajectories to form a neural-fuzzy control structure and used to compensate for nonlinear effects.

To test the performance of the proposed neural fuzzy control method, the angle and the position of the inverted pendulum are

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controlled. Two neural-fuzzy control schemes based on two well-known neural network control schemes such as the FEL and the RCT are studied. Performance of each scheme is compared.

2. Modeling of an Inverted Pendulum

The dynamic model of an inverted pendulum shown in figure 1 is as follows:

$$(M+m)\ddot{x} + mL\ddot{\theta}\cos\theta - mL\dot{\theta}^2\sin\theta + b_x\dot{x} = u \qquad (1)$$

$$(J+mL^2)\ddot{\theta} + mL\ddot{x}\cos\theta - mgL\sin\theta + b_\theta\dot{\theta} = 0 \qquad (2)$$

where M is the mass of the cart (kg), m is the mass of the pendulum (kg), L is the length of a pendulum(m), J is the moment of a pendulum ($kg \cdot m^2$), g is the gravity acceleration (m/s^2), b_x is a friction coefficient of the cart, and b_θ is the friction coefficient of the pendulum .

$\theta, \dot{\theta}, \ddot{\theta}$ are the angle (rad), the angular velocity (rad/s), and the angular acceleration (rad/s^2) of the pendulum, respectively. $x, \dot{x}, \ddot{x}$ are a displacement(m), a linear velocity(m/s), and a linear acceleration (m/s^2) of the cart, respectively.

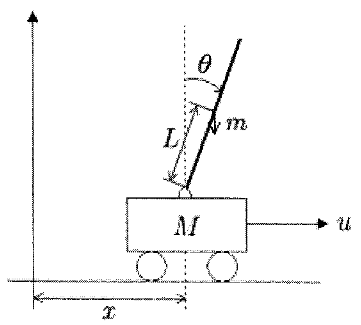

Fig. 1. Inverted pendulum system

3. Fuzzy Control

Inputs to the fuzzy controller are errors of angles, angular velocities, displacements, and linear velocities. The range of the pendulum angle is $-30^\circ \le \theta \le 30^\circ$ and the range of the cart displacement is $-1.5m \le x \le 1.5m$.

Membership functions of control variables such as e_θ, $\dot{e}_\theta$, e_x, $\dot{e}_x$ and a control input u are shown in figure 2 and those values are normalized at [-1, 1]. Here, the generalized PD-like control rules are used.

The fuzzy rule statements are represented as follows:

$R_\theta : If\ e_\theta\ is\ A_i,\ \dot{e}_\theta\ is\ B_i,\ then\ u_\theta\ is\ C_i$

$R_x : If\ e_x\ is\ A_j,\ \dot{e}_x\ is\ B_j,\ then\ u_x\ is\ C_j$

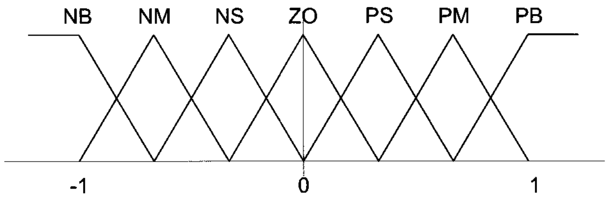

Fig. 2. Membership functions

Rules of the control input u_θ for controlling a pendulum angle consist of e_θ and $\dot{e}_\theta$. Similarly, for the cart, the control input u_x is composed of e_x and $\dot{e}_x$. So, the total 49 rules are used in this case.

For a normalization process, a scaling factor for the angle (θ) is 15 deg, for the angular velocity ($\dot{\theta}$) is 40 deg/sec, for the position (x) is 0.2m, for the linear velocity ($\dot{x}$) is 0.45m/sec. Finally, the scale factor for the control input u is 40. Those values are determined by trial and error process.

4. Neural Compensation for Fuzzy Controlled Systems

4.1. FEL based neural fuzzy control

The control structure of the FEL based fuzzy control is depicted in figure 3 [11-13]. Neural network compensating signals are added to the control input level. Neural network outputs u_n are generated to minimize the system error u_f. The actual control input to the system is the sum of u_f and u_n.

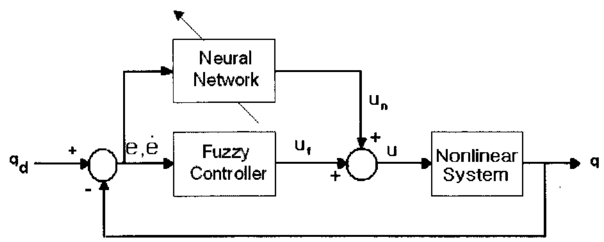

Fig. 3. FEL based neural network-fuzzy control

To adjust a neural network in on-line, the back propagation algorithm is developed. The objective function to be minimized is as follows

$$E = \frac{1}{2} u_f^{\ T} u_f\ , \quad u_f = f(e_\theta, \dot{e}_\theta, e_x, \dot{e}_x) \qquad (3)$$

The control input u is the sum of the fuzzy control u_f and the neural network output u_n.

$$u = u_f + u_n \qquad (4)$$

To obtain the gradient of E with respect to the weight w, we have

$$\frac{\partial E}{\partial w}=\frac{\partial E}{\partial u_f}\frac{\partial u_f}{\partial w}=u_f\frac{\partial(u-u_n)}{\partial u_N}\frac{\partial u_n}{\partial w}=-u_f\frac{\partial u_n}{\partial w} \tag{5}$$

The training signal u_f is available from the fuzzy controller output. Equation (5) can be used in the weight update equation.

4.2 RCT based neural-fuzzy control scheme

The reference compensation technique (RCT) is known as one of the on-line learning algorithms for the neural network training [14-16]. One typical advantage of the RCT is that a neural network can compensate for uncertainties without modifying the internal controllers as shown in figure 4.

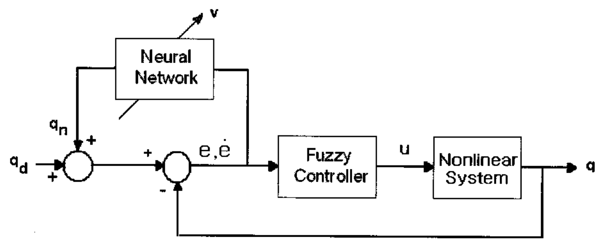

Fig. 4. Reference compensation technique scheme for a fuzzy controlled system.

The error is formed as

$$e=q_d-q+q_n \tag{6}$$

where q_n is output of a neural network. Note that the neural network compensation signal q_n can modify the fuzzy rules.

For example, the typical error value e_1 corresponds to the membership value μ_1 in the PD like fuzzy controller. If the system parameter is varying, μ_1 is a no longer good membership value. Now the optimum membership value is μ_1^*. Here a fuzzy rule has to be modified from μ_1 to μ_1^* with respect to the error value e_1. Adding a neural network compensating signal q_n can modify the fuzzy rule as indicated in equation (6) such that the membership value is changed from μ_1 to μ_1^*.

The output of the fuzzy PD controller can be represented as

$$\begin{aligned} u_f &\cong k_1 e+k_2\dot{e} \\ &=k_1(q_d-q+q_n)+k_2(\dot{q}_d-\dot{q}+\dot{q}_n) \\ &=k_1\varepsilon+k_2\dot{\varepsilon}+k_1 q_n+k_2\dot{q}_n \end{aligned} \tag{7}$$

where k_1, k_2 are constants that are determined by fuzzy rules and $\varepsilon=q_d-q$.

Let u be the control input of the system. Then equation (7) becomes

$$u=k_1\varepsilon+k_2\dot{\varepsilon}+k_1 q_n+k_2\dot{q}_n \tag{8}$$

Rearranging (8) yields

$$k_1\varepsilon+k_2\dot{\varepsilon}=u-(k_1 q_n+k_2\dot{q}_n) \tag{9}$$

Although values of k_1, k_2 are not known exactly, those gains can be selected by user's intuition.

The training signal is defined as

$$v=k_1\varepsilon+k_2\dot{\varepsilon} \tag{10}$$

Note that the training signal can be formed if the system output is available.

The objective function to be minimized is defined as

$$E=\frac{1}{2}v^T v \tag{11}$$

The gradient for the back-propagation algorithm can be obtained as

$$\frac{\partial E}{\partial w}=\frac{\partial E}{\partial v}\frac{\partial v}{\partial w}=-v\left(k_1\frac{\partial q_n}{\partial w}+k_2\frac{\partial \dot{q}_n}{\partial w}\right) \tag{12}$$

There are several modifications of the RCT based control structure depending upon how many outputs are used for neural network outputs such as two outputs θ_N, x_N or four outputs $\theta_N, \dot{\theta}_N, x_N, \dot{x}_N$.

5. Simulation Results

5.1 Simulation setup

The RCT based fuzzy control structure is depicted in figure 5 in detail.

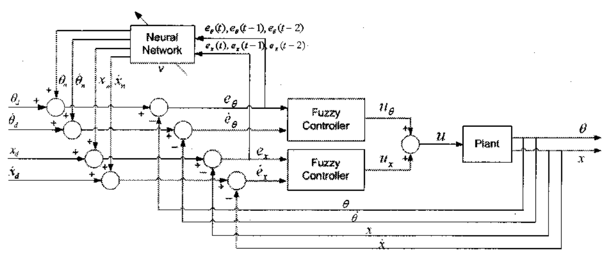

Fig 5. RCT based neural-fuzzy control block

Inputs to neural networks are delayed terms such as $e_\theta(t)$, $e_\theta(t-1)$, $e_\theta(t-2)$, $e_x(t)$, $e_x(t-1)$, $e_x(t-2)$. First, the general PD-like fuzzy control scheme is tested. Although modifying fuzzy rules for an inverted pendulum control may improve the performance better, the generalized PD-like fuzzy controller is used. Second, the FEL based fuzzy control scheme is tested. An output of a neural network is added to the output of the fuzzy controller to compensate. Third, the RCT based fuzzy control scheme is tested. Outputs of a neural network are added to input trajectories. The training signals may have variations. Each scheme is tested for the same control objective of balancing and tracking control of the inverted pendulum.

5.2 Balancing control of the pendulum

1) PD-like Fuzzy control scheme

An initial angle of the pendulum is 7 (deg), and an initial position of the cart is x = 0 (m). A gain for the angle is 20 and for the position is 5. Control performances are shown in figures 6 and 7. The pendulum keeps oscillating within bounds, but successfully maintains the balance.

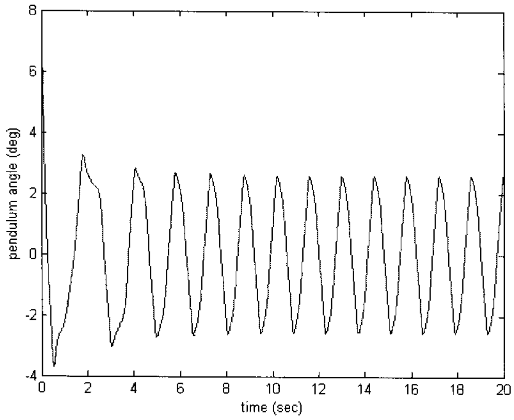

Fig. 6. Pendulum angle of PD like fuzzy control

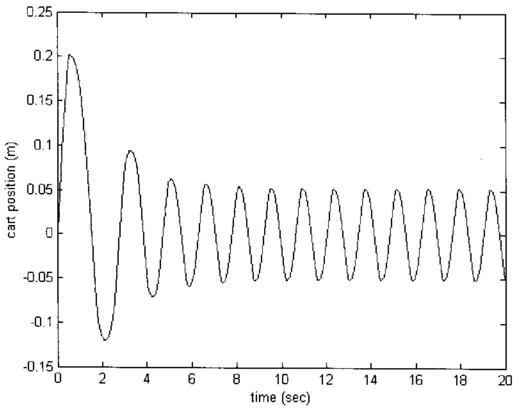

Fig. 7. Cart position of PD like fuzzy control

2) FEL based fuzzy control scheme

The learning rate is 0.05 and a momentum term is 0.1. The number of hidden layer units is 6, and an NN out is multiplied by 5. Figures 8 and 9 show performances by the compensation of the FEL based fuzzy control.

The oscillating errors are minimized compared with a PD-like fuzzy control.

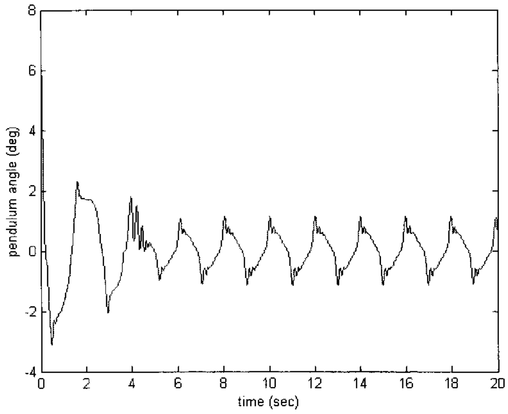

Fig. 8. Pendulum angle of FEL based fuzzy control

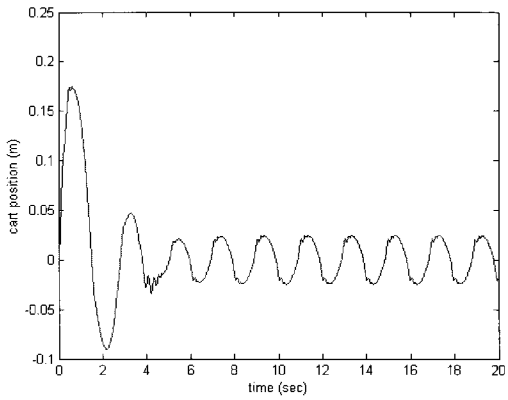

Fig. 9. Cart position of FEL based fuzzy control

3) RCT based fuzzy control

The learning rate is 0.05, a momentum term is 0.1, the number of hidden layer units is 4, and NN outs are scaled down by (1)*1/200, and (2)*1/100. The learning signal is defined as $v = 30 * e_\theta + 0.1 * e_x$. The errors are further minimized as shown in figures 10 and 11.

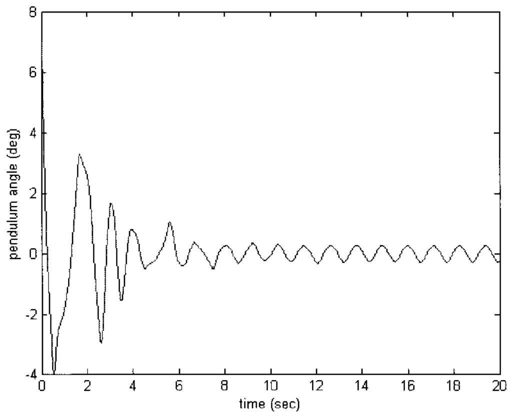

Fig. 10. Pendulum angle of RCT based fuzzy control

The cart positional error is less than $\pm 1cm$. Comparing results of the PD-like fuzzy control with those of the RCT based fuzzy control, the error of the RCT based fuzzy control is gradually minimized.

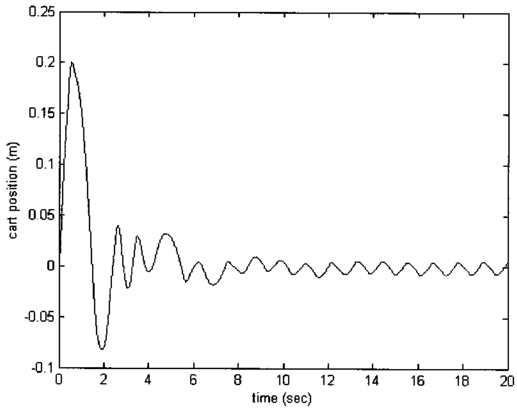

Fig. 11. Cart position of RCT based fuzzy control

5.3 Tracking control of the cart

Next, the desired command for the cart is given as a step function to move 30cm and to come back to the original position.

1) PD-like fuzzy control scheme

Results shown in figures 12 and 13 are quite oscillatory, but it maintains the control. The cart moves toward a desired position well as shown in figure 13. Since the pendulum keeps oscillating, the cart also keeps moving back and forth as shown in figure 13.

2) FEL based fuzzy control scheme

Here, we used $\eta = 0.05$, $\alpha = 0.1$, 6 hidden layer units, and NN out*5.

Compensation by a neural network at torque improves the tracking performance. The errors are minimized in position tracking of the cart. Figures 14 and 15 show that tracking errors are further minimized.

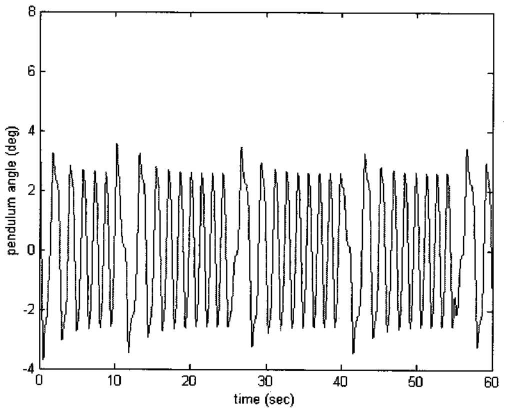

Fig. 12. Pendulum angle of PD-like fuzzy control

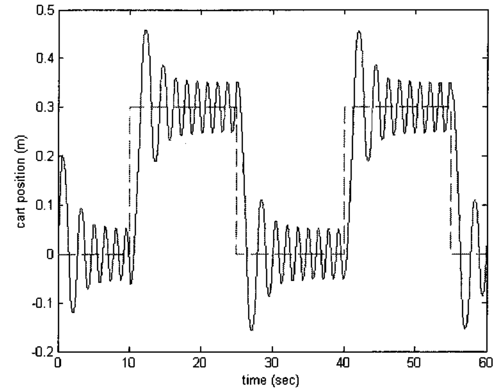

Fig. 13. Cart position of PD-like fuzzy control

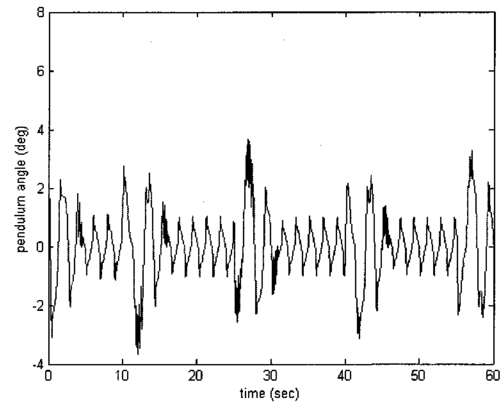

Fig. 14. Pendulum angle of FEL based fuzzy control

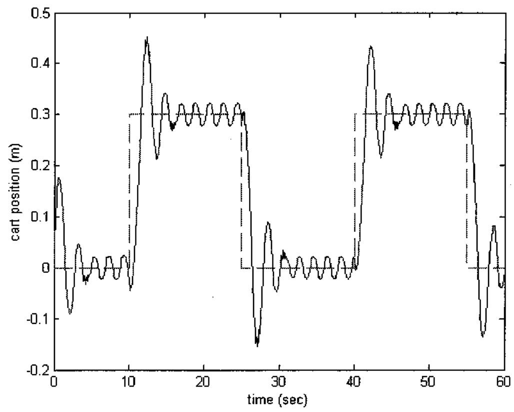

Fig 15. Cart position of FEL based fuzzy control scheme

3) RCT based fuzzy control scheme

We have used $\eta = 0.05$, $\alpha = 0.1$, 4 hidden layer units, NN out(1)*1/200, and NN out(2)*1/100. The training signal is P type as $v = 30 * e_\theta + 0.1 * e_x$. Comparing results shown in figures 16 and 17 with those of figures 14 and 15 show that the performance of the RCT is better in tracking errors. Tracking errors are clearly minimized.

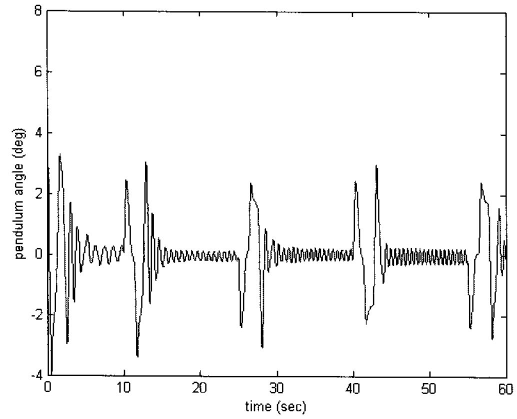

Fig. 16. Pendulum angle of RCT based fuzzy control

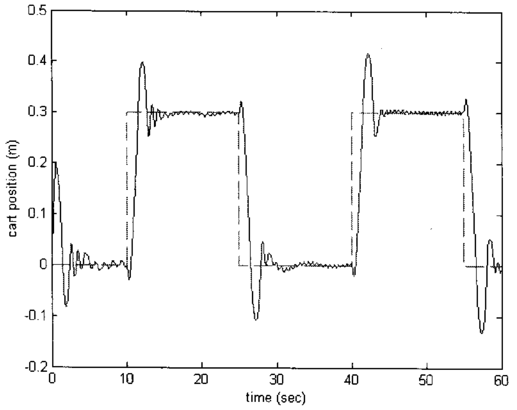

Fig. 17. Cart position of RCT based fuzzy control

6. Conclusion

This paper presents a new method of compensating for uncertainties in the fuzzy controlled nonlinear dynamical system. Neural networks are used as an auxiliary controller for the standard PD-like fuzzy controllers. Two schemes, the FEL based fuzzy control and the RCT based fuzzy control, are tested. Performances of two schemes are better than that of the PD-like fuzzy control by itself. Among several schemes, the RCT based fuzzy control method shows the best performance in controlling the pendulum angle as well as the cart position. This confirms that neural network modifies the fuzzy rules corresponding to the system nonlinearities.

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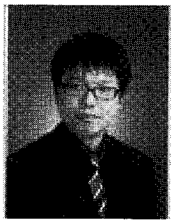

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