Experimental Studies of Neural Compensation Technique for a Fuzzy Controlled Inverted Pendulum System

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Abstract

This article presents the experimental studies of controlling angle and position of the inverted pendulum system using neural network to compensate for errors caused due to fuzzy controller. Although fuzzy control method can deal with nonlinearities of the system, fixed fuzzy rules may not work and result in tracking errors in some cases. First, a nominal Takagi-Sugeno (TS) type fuzzy controller with fixed weights is used for controlling the inverted pendulum system. Then the neural network is added at the reference input to form the reference compensation technique (RCT)control structure. Neural network modifies the input trajectories to improve system performances by updating internal weights in on-line fashion. The back-propagation learning algorithm for neural network is derived and used to update weights. Control hardware of a DSP 6713 board to have real time control is implemented. Experimental results of controlling inverted pendulum system are conducted and performances are compared.

Key Words : RCT, TS fuzzy controller, inverted pendulum.

1. Introduction

Recently, demand of interaction between human beings and systems is rapidly increasing. For systems to have interaction with human beings, some sorts of intelligent communication techniques are required. Intelligent communication between human beings and systems includes vocal communication, visual communication, and physical communication. For those communications, channel is an important factor between two systems.

Fuzzy logic is known as one of powerful communication tools of representing human expression into machine expression. Transferring human knowledge to machines requires mapping between semantic processing and numerical processing such that machines can recognize human meaning. Fuzzy logic can convert vague linguistic human information to a single numerical value for controlling dynamical systems as a physical communication channel.

In the framework of physical communication, fuzzy logic can be used as intelligent controllers for nonlinear systems, complicated systems, and uncertain systems. Fuzzy control has demonstrated successful performances in numerous examples in various control applications. Balancing control of the inverted pendulum system has been successfully demonstrated by fuzzy controllers [1-3]. Fuzzy controllers have been designed for controlling robot manipulators as well.

Although fuzzy controllers work quite well in controlling nonlinear systems, they require time consuming procedure to obtain suitable fuzzy rules for a typical system. Designing fuzzy rules requires knowledge and experiences on the system so that a novice designer may have difficulty of designing rules.

Once fuzzy rules are designed, systems can vary and have outer disturbances. Then poor performance can be expected. To solve this problem, an adaptive fuzzy control method of modifying fuzzy rules has been proposed. The adaptive fuzzy control scheme has a neural network structure whose each layer accomplishes fuzzy function process such as fuzzification, inference, and defuzzification. As a result, fuzzy rules can be adjusted adaptively by the back-propagation learning algorithm [4-8].

In our previous research, the neuro-fuzzy control scheme based on Takagi-Sugeno (TS) fuzzy control structure has been implemented and tested for controlling the pendulum system [9]. In the experimental studies, we have found that initial conditions become important for stability since all the weight values of the neuro-fuzzy controller are selected randomly. Thus a major problem was how to stabilize the system at the beginning[9].

Therefore, in this paper, a different neuro-fuzzy control scheme is presented to address initial stability problem. A nominal fuzzy controller with fixed weights is used as a primary controller. Since fuzzy rules are not optimized, performance may be degraded. We add a separate neural network to change fuzzy rules by modifying reference input values[10]. This forms the reference compensation technique control method as one of neural network control methods that

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has been used for controlling the inverted pendulum system[11-13].

To test the performance of the proposed neuro-fuzzy controller, experimental studies of the inverted pendulum system in the intelligent control educational kit are conducted.

2. TS Fuzzy Control Structure

Fuzzy controller can be described as a gain scheduling linear controller. Infinite number of controller gains can be obtained by the fuzzy controller to mimic look-up tables for different states with respect to uncertainties in the system. Fuzzy controller consists of several steps, defuzzification, inference, and fuzzification procedures to complete the fuzzy controller.

The general fuzzy control structure is shown in Fig.1. Fuzzification process converts numerical crisp values to linguistic fuzzy set. It takes crisp input values $e(t)$ and calculates the membership function $\tilde{e}$. Fuzzy inference process finds appropriate resultant rules based on inference between fuzzy rules. Finally, defuzzification process converts resultant fuzzy information $\tilde{u}$ to a numerical value $u(t)$.

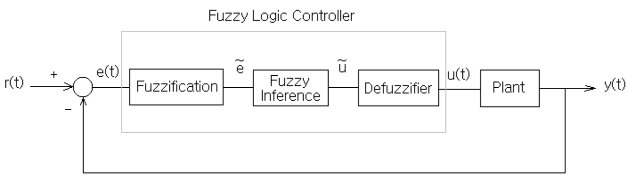

Fig. 1 Fuzzy control structure

TS fuzzy control algorithm uses the linear output instead of using Mamdani fuzzy rule method for the defuzzification process. Although Mamdani fuzzy rule represents if-then structure, mathematical formulation is difficult. But the linearized output representation of the TS structure makes the system be easier, simpler, and computationally faster. The difference is that the resultant part of if rules is linear.

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

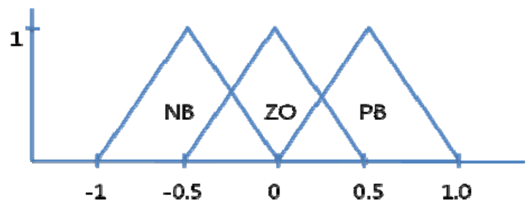

Fig. 2 Membership functions

The fuzzy rule statements of TS scheme are represented as follows:

R_θ : *If* e_θ *is* A_i, $\dot{e}_\theta$ *is* B_i, *then* $u_\theta = p_\theta e_\theta + q_\theta \dot{e}_\theta + r_\theta$

R_x : *If* e_x *is* A_j, $\dot{e}_x$ *is* B_j, *then* $u_x = p_x e_x + q_x \dot{e}_x + r_x$

where p,q,r are constants. The output can be easily formulated in mathematical form which makes possible for applying the back-propagation algorithm.

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 $\dot{e}_x$.

3. RBF Network Structure

As a neural network compensator, the radial basis function(RBF) network is used as shown in Fig. 3. The RBF network is known for fast convergence and mathematically analyzable. It consists of the input, hidden, and output layer as shown in Fig. 3.

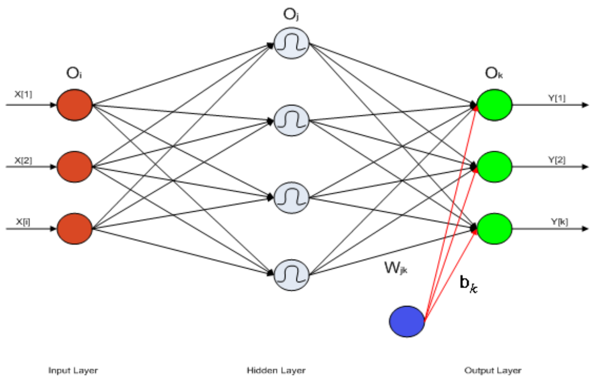

Fig. 3 RBF neural network structure

The hidden layer is nonlinear and the output layer is linear. The nonlinear function used in the hidden layer is the Gaussian function.

$$\varphi_j(X) = \exp\left(-\frac{\| X - \mu_j \|^2}{2\sigma_j^2}\right) \tag{1}$$

where X is the input vector $X = [x_1 x_2 \ldots x_n]^T$, μ_j is the center value vector of the *j*th hidden unit, and σ_j is the width of the *j*th hidden unit.

The forward *k*th output in the output layer can be calculated as a sum of outputs from the hidden layer.

$$y_k = \sum_{j=1}^{M} \varphi_j w_{jk} + b_k \tag{2}$$

where φ_j is *j*th output of the hidden layer in (1) and w_{jk} is the weight between the *j*th hidden unit and *k*th output, and b_k is the bias weight.

4. Neural Compensated Fuzzy Control Scheme

4.1 RCT Control Scheme

A neural network controller has been known as a powerful nonlinear controller so it can be used as a nonlinear controller by itself[11-14]. Combing the neural network with the fuzzy controller is expected to yield the better performance since merits of two intelligent tools are used.

The proposed RCT neuro-fuzzy control scheme is different from the adaptive neuro-fuzzy control methods. The adaptive neuro-fuzzy control structure has a single neural network to conduct fuzzy logic operation in each layer. Here a neural network and a fuzzy controller are separately designed. The radial basis function network is added in cascade to the fuzzy controlled system shown in Fig. 1 as a prefilter.

The neural network compensated fuzzy control structure is shown in Fig. 4. In the proposed scheme, instead of modifying fuzzy rules by weights of neural network directly, effects of changing fuzzy rules can be achieved indirectly since the reference input can be modified with respect to errors by neural network. The input trajectory *R* is modified to *Rn* by the neural network in the way of minimizing the output error $\varepsilon = R - Y$.

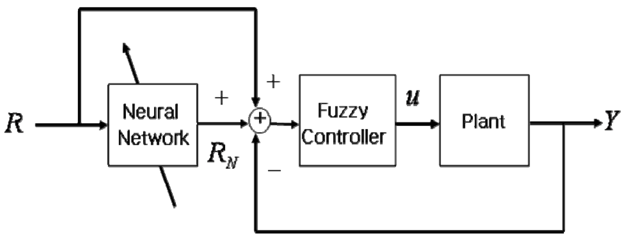

Fig. 4 Neuro-fuzzy control block diagram

Then, the system input error is modified as

$$e = R - Y + R_N \tag{3}$$

where R_N is the output of a neural network. The error e propagates into the fuzzy controller so that the membership function values $\mu(e)$ can be changed with respect to the value of *Rn* due to different input values. The linear output of the fuzzy controller can be represented as

$$\begin{aligned} u &\cong k_1 e + k_2 \dot{e} + k_3 \\ &= k_1 (R - Y + R_N) + k_2 (\dot{R} - \dot{Y} + \dot{R}_N) + k_3 \\ &= k_1 \varepsilon + k_2 \dot{\varepsilon} + k_1 R_N + k_2 \dot{R}_N + k_3 \end{aligned} \tag{4}$$

where k_1, k_2, k_3 are suitable constants selected by intuition and $\varepsilon = R - Y$. Then combining equation (4) with the dynamic equation becomes

$$k_1 \varepsilon + k_2 \dot{\varepsilon} + k_3 + k_1 R_N + k_2 \dot{R}_N = \tau \tag{5}$$

4.2 Control Scheme for inverted pendulum system

The detailed control structure is shown in Fig. 5. One neural network compensates for both angle and position error of the inverted pendulum system. Neural network modifies input values so that we can have effects of changing fuzzy rules.

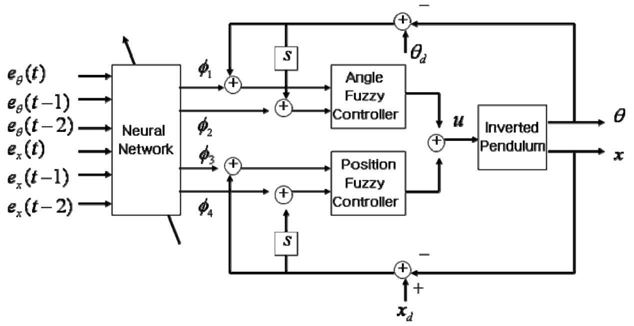

Fig. 5 Neural compensated fuzzy control structure for inverted pendulum system

Then equation (4) can be separated into two fuzzy controller inputs. For the angle control, we have the following control input.

$$\begin{aligned} u_\theta &= k_{\theta 1}(\theta_d - \theta + \phi_1) + k_{\theta 2}(\dot{\theta}_d - \dot{\theta} + \phi_2) + k_{\theta 3} \\ &= k_{\theta 1}\varepsilon_\theta + k_{\theta 2}\dot{\varepsilon}_\theta + k_{\theta 1}\phi_1 + k_{\theta 2}\phi_2 + k_{\theta 3} \end{aligned} \tag{6}$$

where φ_1, φ_2 are neural network outputs.

For the position control,

$$\begin{aligned} u_x &= k_{x1}(x_d - x + \phi_3) + k_{x2}(\dot{x}_d - \dot{x} + \phi_4) + k_{x3} \\ &= k_{x1}\varepsilon_x + k_{x2}\dot{\varepsilon}_x + k_{x1}\phi_3 + k_{x2}\phi_4 + k_{x3} \end{aligned} \tag{7}$$

where φ_3, φ_4 are neural network outputs. Thus, the system control input is given as a sum of two control inputs.

$$u = u_\theta + u_x \tag{8}$$

A single input u has to control both angle and position of the inverted pendulum system. This leads to the difficulty of control.

4.3 Learning Algorithm

Then how to generate output signals of neural network to minimize the error is important problem. Internal weights of the neural network should be updated at every sampling time to minimize the error. Rearranging (6) and (7) yields the error equation as

$$\begin{aligned} & k_{\theta 1}\varepsilon_\theta + k_{\theta 2}\dot{\varepsilon}_\theta + k_{x1}\varepsilon_x + k_{x2}\dot{\varepsilon}_x \\ &= \tau - (k_{\theta 1}\phi_1 + k_{\theta 2}\phi_2 + k_{x1}\phi_3 + k_{x2}\phi_4 + k_{\theta 3} + k_{x3}) \end{aligned} \tag{9}$$

Selecting the learning signal as (10) drives the inverse dynamic control that identifies the inverse system by neural network.

$$v = k_{\theta 1}\varepsilon_\theta + k_{\theta 2}\dot{\varepsilon}_\theta + k_{x1}\varepsilon_x + k_{x2}\dot{\varepsilon}_x \tag{10}$$

However, k_1, k_2 are unknown values that are assumed to be determined from fuzzy logic.

$$v = \tau - (k_{\theta 1}\phi_1 + k_{\theta 2}\phi_2 + k_{x1}\phi_3 + k_{x2}\phi_4 + k_{\theta 3} + k_{x3}) \quad (11)$$

Thus, in real application, suitable values of k_1, k_2, k_3 can be selected although values are not exact. The approximation error is not a problem since the learning rate η of neural network has the linear relationship with the learning signal v and can be optimized by trial and error procedure.

The objective function to be minimized is defined as

$$E = \frac{1}{2} v^2 \quad (12)$$

Differentiating (12) yields the gradient with respect to weights, w($w_{jk}, \theta_k, \mu_j, \sigma_j$) as

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial v}\frac{\partial v}{\partial w} = v\frac{\partial v}{\partial w} = -v\left(\frac{\partial \Phi_\theta}{\partial w} + \frac{\partial \Phi_x}{\partial w}\right) \quad (13)$$

where $\frac{\partial \Phi_\theta}{\partial w} = k_{\theta 1}\frac{\partial \phi_1}{\partial w} + k_{\theta 2}\frac{\partial \phi_2}{\partial w}$, $\frac{\partial \Phi_x}{\partial w} = k_{x1}\frac{\partial \phi_3}{\partial w} + k_{x2}\frac{\partial \phi_4}{\partial w}$.

The weights are updated a s

$$\Delta w(t) = \eta \frac{\partial \Phi}{\partial w} v + \alpha \Delta w(t-1), \quad (14)$$

$$w(t+1) = w(t) + \Delta w(t), \quad (15)$$

where α is the momentum constant for helping the faster convergence of the error. The detailed weight updates for (14) are given by

$$\Delta w_{jk} = \eta_c k_i v_k \varphi_j$$

$$\Delta \theta_k = \eta_b k_i e_k$$

$$\Delta \mu_j = \eta_\mu k_i \varphi_j \sum_{i=1}^{N_I} \frac{(x_i - \mu_j)}{\sigma_j^2} \sum_{k=1}^{N_o} v_k w_{jk} \quad (16)$$

$$\Delta \sigma_j = \eta_\sigma k_i \varphi_j \sum_{i=1}^{N_I} \frac{(x_i - \mu_j)^2}{\sigma_j^3} \sum_{k=1}^{N_o} v_k w_{jk}$$

where N_I is the number of input neurons in the input layer and N_o is the number of output neurons in the output layer.

5. Experimental Studies

5.1 Experimental Setup

Fig. 6 shows the overall inverted pendulum system for the educational purpose. The system consists of the pendulum, control hardware, and a power system. Movements of the cart and the pendulum can be measured by encoders mounted on the rotating axis. Control hardware is shown in Fig. 7 It consists of an FPGA, a DSP, and motor drivers.

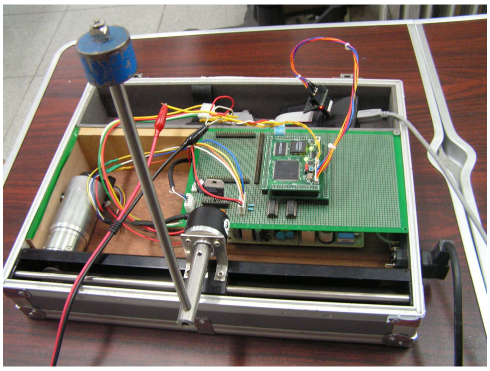

Fig. 6 Overall system setup

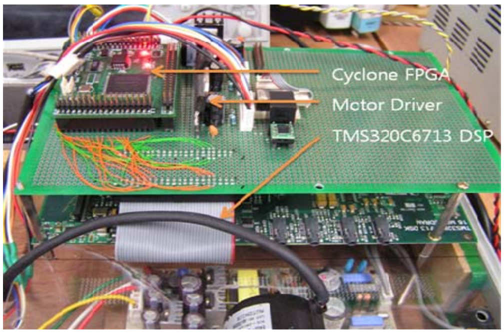

Fig. 7 Control hardware

The block diagram of the system is shown in Fig. 8. The fuzzy controller embedded on a DSP 6713 board communicates with the FPGA module including encoder counters, PWM generators and ADC.

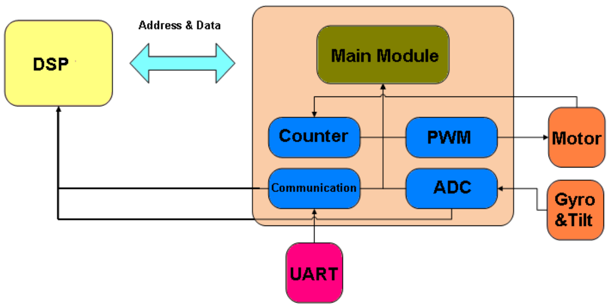

Fig. 8 Overall system block diagram

For the fuzzy controller, we have the following normalized values as listed in Table 1. Table 2 shows the values of linear parameters.

Table 1. Normalization maximum value.

	e_θ	Δe_θ	e_x	Δe_x
value	1 rad	10 rad/s	1 m	10 m/s

Table 2. TS Fuzzy parameters

	k_1	k_2	k_3
Angle	200	2	0
Position	100	50	0

Initial values of learning for neural network are listed in Table 3.

Table 3. Neural-network gains

Learning rates	value
η_w	0.0000001
η_b	0.0000001
η_u	0.000001
η_σ	0.000001

5.2 Trajectory tracking task

The pendulum is required to maintain balancing while the cart follows the desired trajectory. Initially, the fuzzy controller is tested to control the pendulum. Without modifying the values of linear output parameters in defuzzification process, the pendulum becomes unstable. Thus, linear output values are modified to stabilize the system. The parameter values are selected as listed in Table 2.

Fig. 9 shows the actual sinusoidal trajectory tracking results by two control schemes. Two control schemes work well. The corresponding error plots are shown in Figs. 10 and 11.

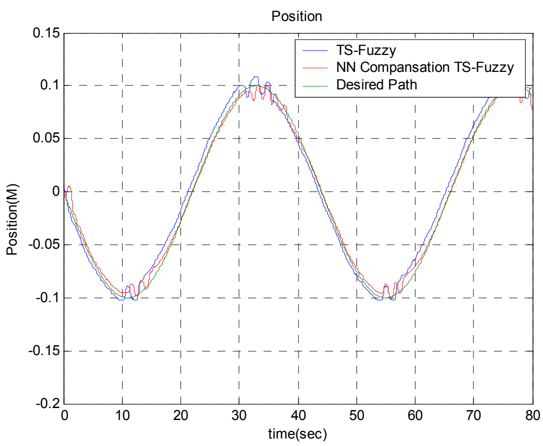

Fig. 9 Position tracking result of the cart

Fig. 10 shows the angle error of the fuzzy controller. The corresponding position error is shown in Fig. 11. It is clearly shown that the position error of the proposed scheme is much smaller than that of the fuzzy controller. This confirms that neural network plays a role to minimize the tracking errors further.

Fig.12 shows the corresponding compensation signals generated from the neural network. To clearly show the better performance by the proposed controller, the RMS errors are listed in Table 4.

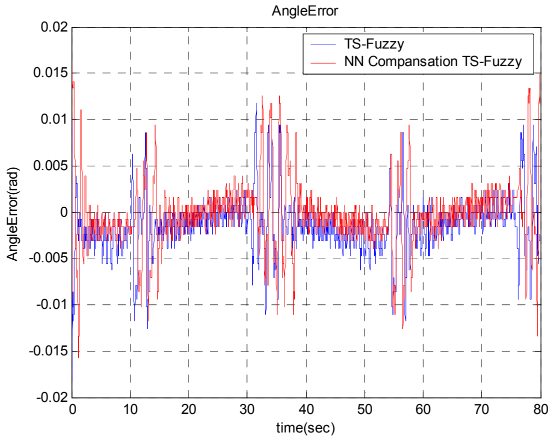

Fig 10. Angle error of the pendulum

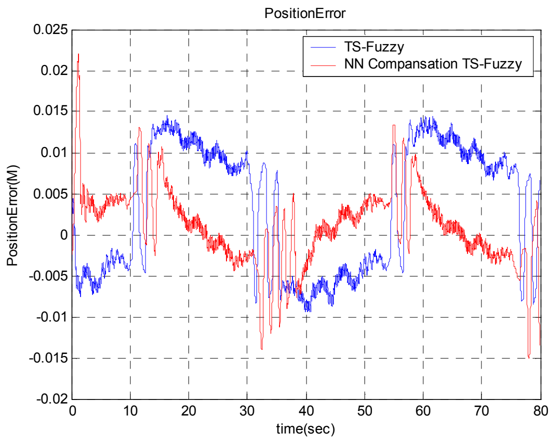

Fig 11. Position error of the inverted pendulum

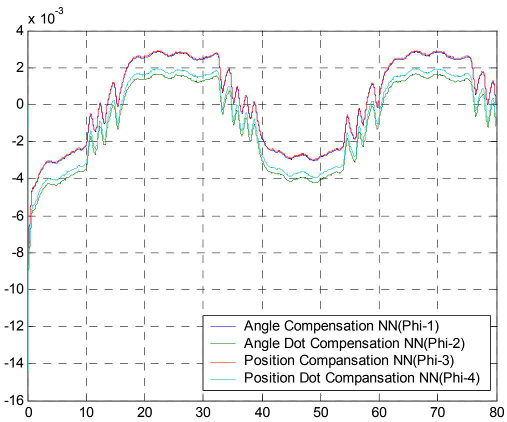

Fig. 12 Compensation signals

Table 4. RMS errors

	Angle	Position
TS-Fuzzy	0.0032632	0.0084062
RCT TS-Fuzzy	0.0036190	0.0048458

6. Conclusion

The RBF neural network is added to the fuzzy controlled system to improve the performance. Although the adaptive fuzzy controller performs well, the new scheme is tested for the case where internal weights of fuzzy controller are fixed. The inverted pendulum system in the educational kit has been tested for the controller performances. In the proposed control scheme, control performance has been improved without a burden of finding optimal fuzzy rules. Experimental results show the better tracking performance by the proposed control scheme. This confirms that the neural controller plays quite an important role to improve the system performance by forming a neuro-fuzzy control structure.

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