REDUCING STEADY-STATE ERRORS OF A DIRECT DRIVE ROBOT USING NEUROFUZZY CONTROL

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Abstract: *This paper presents an effective approach for reducing steady-state errors of robotic manipulator. Although a conventional fuzzy controller has been widely applied for motion tracking of robotic manipulators, their position errors and velocity errors usually still remain at the steady states. To compensate the output of the fuzzy controller, a trained neural network was integrated at the feedforward path to predict a desired actuating torque at the steady state. After implementing this concept on a direct drive SCARA robot, the experimental results showed that the position errors at the steady state were significantly reduced compared to those obtained from a conventional fuzzy controller.*

1. INTRODUCTION

Since the dynamics of the robotic manipulator is highly nonlinear and time varying, various advanced control theories including fuzzy control have been developed for the robotic manipulator to increase the control performance [1,2]. Fuzzy control does not necessarily depend on the accuracy of the plant model. However, it is based on the heuristics about the plant behaviors. Furthermore, its underlying logic is quite similar to human decision making [3].

Fuzzy set theory was first introduced by L.A. Zadeh to deal with imprecise objects whose behaviors are too complex or ill defined to admit of precise mathematical analysis [4,5]. He suggested various possible application fields of fuzzy set theory which is based on the use of linguistic variables and fuzzy algorithms. A good survey of the fuzzy logic controllers was also presented by Lee [6]. Wang reviewed fuzzy control theory as a subset of nonlinear control theory [3]. He also pointed out that the control performance of a fuzzy controller is better than one of a conventional PID controller due to its nonlinear behavior.

Comparing with the other industrial processes, motion control problems require faster and more accurate response. The applications of fuzzy logic motion control problems were reported intensively in the literature [2,3,6]. Huang and Tomizuka applied fuzzy controller to two-dimensional motion tracking system whose tracking precision and travel time were improved compared to those obtained from the conventional PD controller [7]. Kang and Kwak applied fuzzy control to the motion tracking control of direct drive robotic manipulators, and showed that the position tracking performance of fuzzy control was similar to or often better than the one of PID control through simulation and experimental studies [2]. In their studies, the fuzzy controller

has two input variables, a position error and a velocity error, and some position errors always remain at the steady state conditions such as at the end points of robot's trajectory.

Since a neural network can handle complex input-output relationships without detailed analytical models, it is well suited to avoid modeling difficulties for complex physical system. Furthermore, artificial neural network posses an inherent nonlinear structure suitable for nonlinear mapping, modeling, and controlling of nonlinear dynamic systems [8, 9]. Hence, it could be integrated with the fuzzy systems to improve the overall performance.

This paper presents a neurofuzzy control algorithm for reducing the position errors existing at the steady state in the motion control of robotic manipulator. The experimental studies were also conducted for the two axes direct drive SCARA robot to evaluate the control performance.

2. ROBOT ARM DYNAMICS AND MODELING

A robot manipulator is defined as an open kinematic chain of rigid links. Each degree of freedom of the manipulator is powered by independent torque. Using the Lagrangian formulation, the equations of motion of an *n*-degree-of-freedom manipulator can be written as

$$D(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F_r(\dot{q}) + \tau_d = \tau \qquad (1)$$

where $q \in R^n$ is the generalized coordinates; $D(q) \in R^{nxn}$ is the symmetric, bounded, positive-definite inertia matrix; vector $C(q,\dot{q})\dot{q} \in R^n$ presents the centrifugal and Coriolis torque; $G(q) \in R^n$, $F_r(\dot{q}) \in R^n$, $\tau_d \in R^n$, and $\tau \in R^n$ represent the gravitational torque, friction, disturbance, and applied joint torque, respectively.

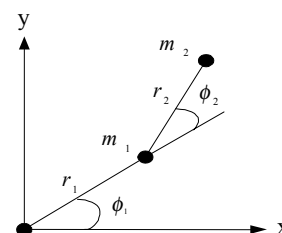A model of two-axis SCARA robot is shown in Fig. 1.

Fig. 1. Model of two-axis SCARA robot

The dynamic equation can be derived by using the Euler-Lagrangian method as follows:

$$\begin{bmatrix} D_{11}(\phi_2) & D_{12}(\phi_2) \\ D_{21}(\phi_2) & D_{22}(\phi_2) \end{bmatrix}\begin{bmatrix} \ddot{\phi}_1 \\ \ddot{\phi}_2 \end{bmatrix} + \begin{bmatrix} -C_{12}(\phi_2)\dot{\phi}_2 & -C_{12}(\phi_2)(\dot{\phi}_1 + \dot{\phi}_2) \\ C_{12}(\phi_2)\dot{\phi}_1 & 0 \end{bmatrix}\begin{bmatrix} \dot{\phi}_1 \\ \dot{\phi}_1 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} \quad (2)$$

where

$$D_{11}(\phi_2) = (m_1 + m_2)r_1^2 + m_2 r_2^2 + 2m_2 r_1 r_2 \cos(\phi_2)$$

$$D_{12}(\phi_2) = D_{21}(\phi_2) = m_2 r_2^2 + m_2 r_1 r_2 \cos(\phi_2)$$

$$D_{22}(\phi_2) = m_2 r_2^2$$

$$C_{12}(\phi_2) = m_2 r_1 r_2 \sin(\phi_2)$$

The parameter values for SCARA robot in experiment are

$$r_1 = 0.50\,m \qquad r_2 = 0.35\,m$$
$$m_1 = 54.21\,kg \qquad m_2 = 17.99\,kg$$

Fig. 2. SCARA robot manipulator used in experiment

3. THE STRUCTURE OF NEUROFUZZY CONTROLLER

A position error due to Coulomb friction, etc. generally remains at the steady state conditions in the position control of mechanical systems such as robotic manipulators. Conventional fuzzy controller using two input variables, position error and velocity error, cannot remove such an error existing at the steady state conditions [2]. Since the neural network (NN) can learn a non-linear mapping of the system model, it could enhance the performance of fuzzy control. The proposed neurofuzzy controller structure for robot control is shown in Fig. 3. This scheme consists of a fuzzy controller and a feedforward neural controller. The fuzzy controller makes the overall system stable along a desired trajectory. In the feedforward path, NN is also used to predict the desired actuating torque.

Since the position errors at the steady state are generally small, we activate the NN only at the steady state condition to remove the small position errors effectively. The steady state is determined from the condition that the variation of position errors during one sampling period is smaller than a threshold value and the position error is smaller than the maximum steady state position error. If the steady state is detected, the NN is switched to feedforward path of the controller.
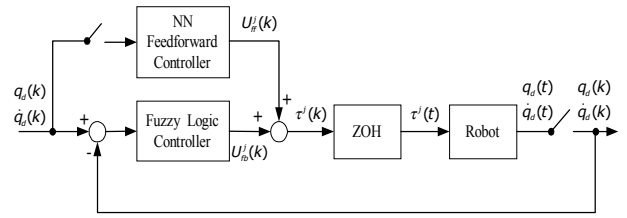

Fig. 3. Scheme of neurofuzzy controller

4. DESIGN OF A FUZZY CONTROLLER

4.1 Fuzzy Controller
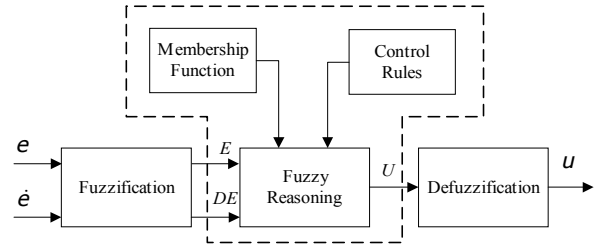The structure of the fuzzy logic controller is shown in Fig. 4.

Fig. 4. The structure of the fuzzy controller

The input variables of the fuzzy controller are angular position error e *(rad)* and angular velocity error $\dot{e}$ *(rad/s)*, which are defined as follows:

$$e = \text{position command - actual position}$$
$$\dot{e} = \frac{e(kT) - e((k-1)T)}{T}$$

where T represents a sampling time. The output variable of the fuzzy controller is the control input u *(N.m)* to the motor driver. In the fuzzy controller, the measured e and $\dot{e}$ values are scaled to some real numbers in the interval of [-1 1] and are mapped to linguistic variables *E and DE* by the *fuzzification* operator. The values of linguistic variables are composed of linguistic terms *PL (Positive Large), PS (Positive Small), ZO (Zero), NS (Negative Small),* and *NL (Negative Large)* which are all fuzzy sets. This set of linguistic terms forms a *fuzzy partition* of input and output spaces. The *knowledgebase* of the fuzzy logic controller is composed of a *database* and a *rule base*. The database defines membership functions for the above linguistic terms and the rule base represents fuzzy control rules.

The membership functions of the fuzzy sets and the fuzzy control rules have a big effect on control performance. Fig. 5. shows the membership functions of the fuzzy sets for the position errors, velocity errors, and control inputs.
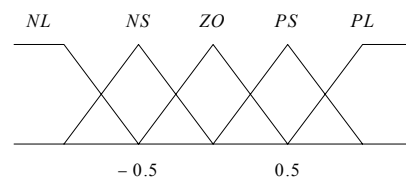

Fig. 5. Membership functions of the fuzzy sets for position errors , velocity errors , and control inputs

The whole fuzzy control rules for the fuzzy logic controller of the direct drive robot are shown in Table 1.

E / DE	NL	NS	ZO	PS	PL
NL	NL	NL	NL	NS	ZO
NS	NL	NL	NS	ZO	PS
ZO	NL	NS	ZO	PS	PL
PS	NS	ZO	PS	PL	PL
PL	ZO	PS	PL	PL	PL

Table 1 The fuzzy control rules for the position control of the robotic manipulator

Among many defuzzification strategies, we adopt the center average method [3] as follows:

$$U = \frac{\sum_i \overline{U}_i \bullet \mu(\overline{U}_i)}{\sum_i \mu(\overline{U}_i)} \qquad (3)$$

where i is the index of the control rule, and $\overline{U}_i$ is the center of the fuzzy set U_i. *Defuzzification* is a mapping from fuzzy control actions into crisp control actions.

5. DESIGN OF A NEURAL NETWORK FEEDFORWARD CONTROLLER

The aim of the NN feedforward compensation term in Fig. 3. is to find a network which can accurately learn the robot inverse dynamics and thus can provide approximation of the non-linear function $U_{ff}^j(k)$. To achieve this, an off-line training process is needed. Thus, an iterative neural learning controller is then operated in two periods; training period and control period.
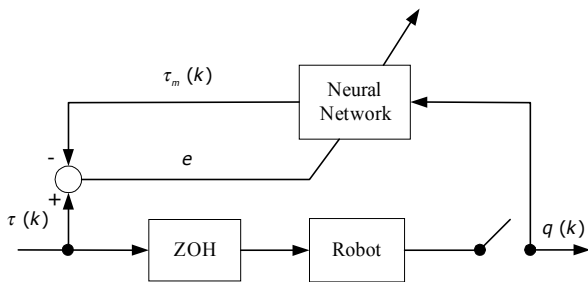

Fig. 6. Training scheme of neural network

During the training period, the universal approximation property of NN is exploited to estimate the robot inverse dynamics, based on the input-output pairs gathered in the (j-1)[th] operation cycle. The NN consists of three layers: 4 neurons in the input layer, 9 neurons in the hidden layer, and 2 neurons in the output layer as shown in Fig. 7. The training data was generated from the robot operation only at the steady state conditions. The weight-tuning algorithm is backpropagation. During the control period, the weights of the well-trained NN controller are fixed and the NN then provides feedforward control signal to compensate for the repeatable uncertainty and non-linear effects.
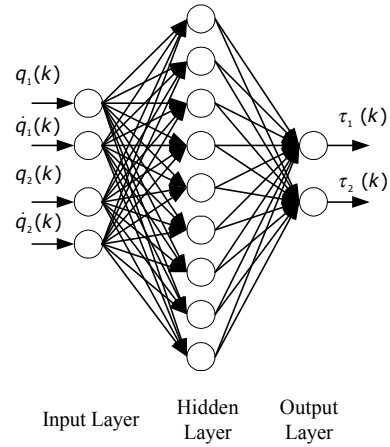

Fig. 7. The structure of the neural network

6. Experimental Results

To verify that the proposed neurofuzzy controller significantly reduces the steady state position errors, the experimental studies were conducted for a two-axis direct drive SCARA robot. The desired trajectory for both axes was given by a fifth order polynomial as shown in Fig. 8. The sampling time T was set to 5 *msec*.
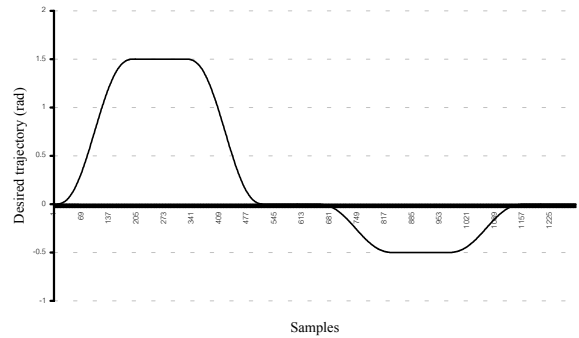

Fig. 8. Desired position trajectory for both axes

Fig. 9 and Fig. 11 showed the position errors from the experiment when conventional fuzzy control was applied. As shown in Fig. 10 and Fig. 12, the proposed neurofuzzy control significantly reduced the steady state position errors more than the conventional fuzzy control did. It also gave the similar position tracking errors to the conventional fuzzy control at the transient response intervals.
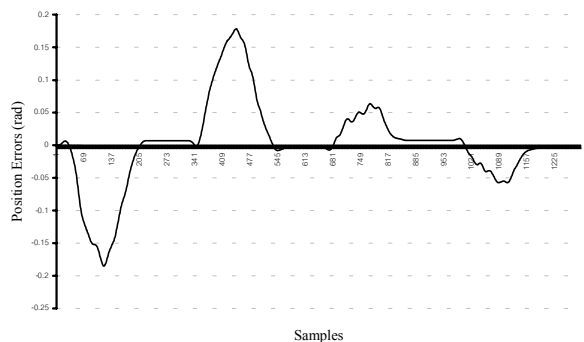

Fig. 9. The position tracking errors of the first axis when the conventional fuzzy controls was applied
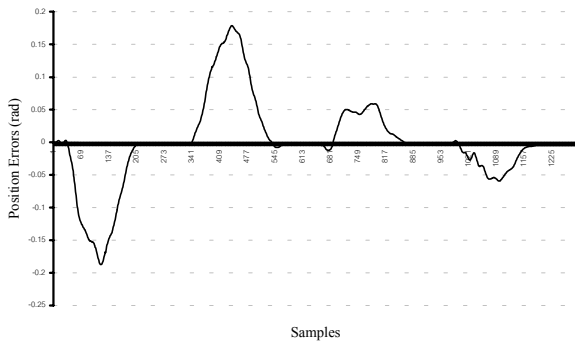
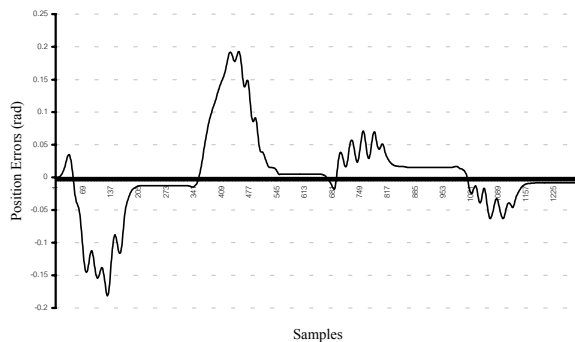Fig. 10 The position tracking errors of the first axis when the proposed neurofuzzy controls was applied

Fig. 11 The position tracking errors of the second axis when the conventional fuzzy controls was applied.
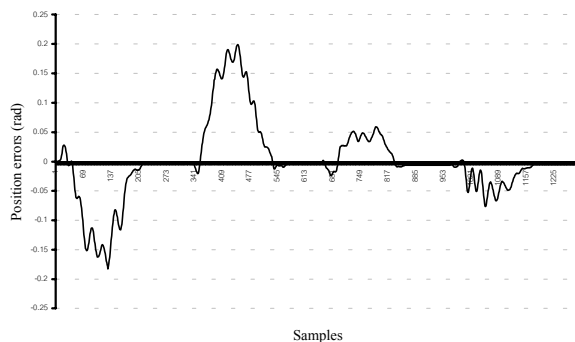

Fig. 12 The position tracking errors of the second axis when the proposed neurofuzzy controls was applied

7. CONCLUSIONS

Conventional fuzzy controllers for the motion tracking of robotic manipulators utilize two input variables, position errors and velocity errors, to deal with highly nonlinear and time-varying dynamics associated with robot motion. However, position errors usually remain at steady state condition due to the Coulomb friction, and etc. In order to reduce the steady state position errors, a neurofuzzy control algorithm was proposed by adding a NN as the feedforward path of controller. The experimental results showed that the position errors at the steady state of the proposed control were significantly reduced compared with the ones of a conventional fuzzy control.

8. REFERENCES

[1]   F. L. Lewis, C. T. Abdallah and D. M. Dawson, *Control of Robotic Manipulators,* Macmillan Publishing Co., 1993.

[2]   C. G. Kang and H. S. Kwak, 1994, "Fuzzy logic control for direct drive robot manipulators," *Proc. Korean Automatic Control Conference,* International vol. 1, pp. 428-433, 1994.

[3]   L. X. Wang, *Adaptive Fuzzy System and Control: Design and Stability Analysis,* Prentice-Hall, 1994.

[4]   L. A. Zadeh, "Fuzzy sets," *Informat. Control,* vol. 8, pp. 338-353, 1965.

[5]   L. A. Zadeh, "Outline of a new approach to the analysis complex systems and decision processes," *IEEE Trans. Syst. Man Cybern.,* vol SMC-3, pp. 28-44, 1973.

[6]   C. C. Lee, "Fuzzy logic in control system: Fuzzy logic controller-Part I, II," *IEEE Trans. Syst. Man Cybern.,* vol. 20, no. 2, pp. 404-435, 1990.

[7]   L. J. Huang and M. Tomizuka, "A self-paced fuzzy tracking controller for two-dimensional motion control," *IEEE Trans. Syst. Man Cybern.,* vol. 20, no. 5, pp. 1115-1124, 1990.

[8]   Kumpati S. Narendra and Kannan Pathasarathy, "Identification and Control of Dynamical Systems Using Neural Networks," *IEEE Trans. Neural Networks,* vol. 1, March 1990.

[9]   Tomochika Ozki, et al, "Trajectory Control of Robotic Manipulators Using Neural Networks," *IEEE Trans. Industrial Electronics,* vol. 38, No. 3. pp. 195-202, June 1991.

[10]   W. K. Hornik and M. Stinchombe, "Multilayer Feedforward Networks Are Universal Approximators," *Neural Networks,* vol. 2, pp. 359-366, 1989.

[11]   Fu-Chuang Chen "On the Error and Parameters Convergence of Back-Porpagation Learning," *IEEE Int. Joint control conference on neural networks,* vol. 2, pp. 1092-1097, 1991.

[12]   Chul. G. Kang and Hee. S. Kwak, "A Fuzzy Control Algorithm Reducing Steady-State Position Errors of Robotic Manipulators," *IEEE Int. Workshop on Advance Motion Control,* pp. 121-126, 1996.