

Implementation of an Adaptive Robust Neural Network Based Motion Controller for Position Tracking of AC Servo Drives

Won-Ho Kim

Department of Mechatronics Engineering, Dong-Eui University
995 Eomgwang-ro, Busanjin-gu, Busan 614-714, Korea
Tel : +82-51-890-2260, Fax : +82-51-890-2255, E-mail : kwh@deu.ac.kr

Abstract

The neural network with radial basis function is introduced for position tracking control of AC servo drive with the existence of system uncertainties. An adaptive robust term is applied to overcome the external disturbances. The proposed controller is implemented on a high performance digital signal processing DSP TMS320C6713-300. The stability and the convergence of the system are proved by Lyapunov theory. The validity and robustness of the controller are verified through simulation and experimental results

Key Words : Adaptive Robust Neural Network, AC Servo Drives, DSP based, Motion Controller.

1. Introduction

In the last few decades, AC servo drives have been extensively used in the industrial market. Along with their intensive applications, many works have been conducted to try to enhance the performance of the motion control system. In [1] and [2], the authors developed an auto-disturbance rejection controller to achieve high performance and large robustness motion control. H.W.Kim et al. [3] introduced an optimal full order estimator based on Kalman filter to estimate the instantaneous speed and position. H.L Huy [4] designed a direct fuzzy controller and fuzzy logic based adaptation mechanism for the AC servo drives which was able to compensate for the disturbance and accommodate to changing load conditions. In [5] and [9], the authors successfully presented a back propagation neural network to identify the dynamic parameters of AC servo motor. Y.T.Kim [6] proposed an adaptive fuzzy back-stepping scheme to solve the position tracking problem of an AC servo motor with the non-uniform LuGre friction. In this paper, the asymptotic stability was guaranteed, and the controller was able to overcome the parameter uncertainties. In [7], Amin Suyitno et al. developed an effective variable-structure robust controller based on the fuzzy logic mechanism which was large robust and insensitive to the external disturbances and noises. In [8], an adaptive back-stepping control of AC servo motor was introduced to solve the position tracking problem. In this paper, the control system is implemented in a low cost DSP controller, TMS320C32. In order to improve tracking performance and robustness of motion control system, a robust fuzzy neural network sliding-mode controller was presented [11]. In this work, a fuzzy neural network was adopted to estimate a non-linear function in which the lumped uncertainty of the controlled plan is included. Then, an adaptive scheme was used

to adjust the uncertainty term in the robust controller according to the function of the sliding surface. M. W. Naouar et al. [12] introduced a variety of current control techniques using field-programmable gate array (FPGA) components to apply to the alternating current machine drive.

In most cases of the previous approaches, the authors have successfully constructed the robust motion controller [1], [2] to suppress the disturbances or the neural network to identify the system parameters [5], [9]. However, in these papers the stability was not guaranteed. On the other hand, the adaptive mechanisms with the proof of asymptotic stability in [6]-[8] and [11] were complex in practical applications.

In this paper, we introduce a simple adaptive robust neural network scheme to overcome such described drawbacks. The main aim of our controller is to define an augment error related to the angular position error and angular velocity error. Then the controller is designed so that the augment error can converge toward zero asymptotically. This process will make the angular velocity error and angular position error stable asymptotically. The controller is able to guarantee the convergence and stability of the servo system despite the existence of model uncertainties and external disturbances. In this controller, a 2-layer neural network with radial basis function is used to approximate the nonlinear factors of the AC servo motor. An adaptive robust control scheme is applied to suppress the disturbances and guarantee the stability of the system. In order to confirm the effectiveness and the validity of our controller, we develop an embedded motion controller based on a high performance floating point DSP TMS320C6713-300 and a CPLD Xilinx XC95288XL. The closed-loop controller and motion profile generators are implemented in the DSP, while the feedback position signals with digital filter and digital inputs/outputs are carried out in the CPLD for real-time multi-axis applications. Afterward, the output current control is put forward to the Elmo analog amplifier to drive the motor.

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2. Adaptive Robust Neural Network Controller

This section introduces the design of proposed controller for the AC servo drive and the proof of stability.

2.1 Modeling of AC Servo Drive

Dynamic equation of an AC servo drive can be described as following:

$$J\dot{\omega} + B\omega + \tau_d = \tau \quad (1)$$

where ω is angular velocity of the rotor, J is the moment of inertia, B is the viscous coefficient. τ is the driving torque, τ_d can be considered as the unknown load torque disturbance on the rotating shaft.

In the system design, it is assumed that the reference angular position is a continuous and differentiable signal. Therefore, the angular velocity and angular acceleration can be expressed as:

$$\omega = \dot{\theta} \quad (2)$$

$$\dot{\omega} = \ddot{\theta} \quad (3)$$

where θ is the angular position.

The goal of our control scheme is to achieve asymptotic tracking for a given continuous reference trajectory.

2.2 Introduction of Feed-forward Neural Network with Radial Basis Function

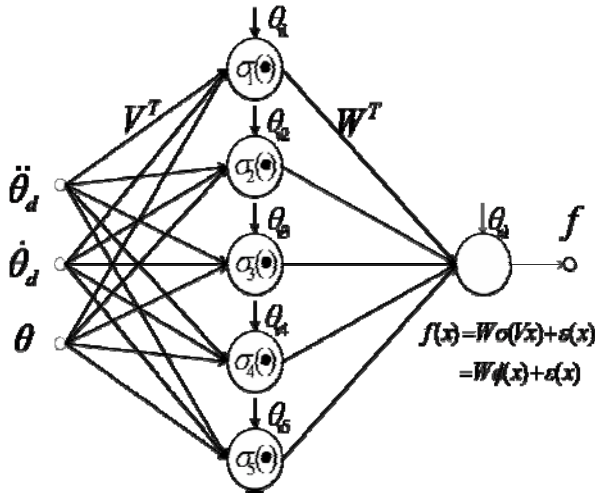


Fig. 1 Two-layer feed-forward neural network.

Two-layer feed-forward neural network can be presented in matrix form:

$$y = W\sigma(Vx) \quad (4)$$

where $W = [w_{ij}]$ and $V = [v_{jk}]$ are the weight vectors, $x = [1, x_1, \dots, x_{N_1}]^T$ is the input vector, $y = [y_1, y_2, \dots, y_{N_2}]^T$ is the output vector, and $\sigma = [1, \sigma_1, \sigma_2, \dots, \sigma_{N_2}]$ denotes the activation

function vector. Constant 1 included in the vector x and σ as a first term allows one to incorporate the thresholds θ_j^v and θ_i^w .

The well-known universal approximation property of a neural network proposed by Hornik et al. [10] says that for a nonlinear function $f(x)$, there exists a sufficiently large N_2 number of neurons satisfying

$$f(x) = W\sigma(Vx) + \varepsilon(x) \quad (5)$$

and makes the two-layer neural network functional approximation error vector $\varepsilon(x)$ arbitrarily small.

We know that the main disadvantage of the multilayer neural network is highly nonlinear in parameter. Hence, we consider hereafter the neural network of fixed V , which makes the neural network linearly parameterized. Defining $\phi(x) = \sigma(Vx)$, we have

$$f(x) = W\phi(x) + \varepsilon(x) \quad (6)$$

where $\phi = [\phi_1, \phi_2, \dots, \phi_{N_2}]$ is the generalized basis function vector. In this paper, we use the radial basis function with Gaussian form as following:

$$\phi_i(x) = \exp\left(-\frac{\|x - o_i\|^2}{2\sigma_i^2}\right), i = 1..N_2 \quad (7)$$

where o_i is the center of the i -th radial basis function, and σ_i is the width coefficient.

2.3 Controller Design

In this section, we introduce the design of proposed controller for AC motor based on the Lyapunov's stability theorem. The strategy is to define an augment error and design a neural network with learning rules and an adaptive robust term to force the augment error to converge to zero asymptotically in spite of the presence of the system uncertainties and load torque disturbances.

The controller scheme is shown in Fig.2 and the angular position tracking error is denoted as:

$$e_\theta = \theta_d - \theta \quad (8)$$

where θ_d is the desired angular position.

Differentiating (8) with respect to time to get the angular position tracking error:

$$e_\omega = \omega_d - \omega \quad (9)$$

The angular velocity tracking error is presented as following:

$$\dot{e}_\theta = \dot{\omega}_d - \dot{\omega} \quad (10)$$

In order to solve the position tracking problem with asymptotical stability, we define the augment error as below:

$$s = e_\omega + \lambda e_\theta \quad (11)$$

Differentiating (11) and substituting it into dynamic equation

(1), we have the error dynamic equation:

$$J\dot{s} = J\theta_d^{\otimes} + B\theta^{\otimes} + J\lambda e_{\omega} - \tau + \tau_d \quad (12)$$

The nonlinear function containing the dynamic parameters of AC servo motor is defined as:

$$f(x) = J\theta_d^{\otimes} + B\theta^{\otimes} + J\lambda e_{\omega} \quad (13)$$

It is well-known that the neural network is capable of approximating any nonlinear function over compact input space [10]. The strategy is to construct a simple neural network with radial basis function as presented in section II.B to approximate the nonlinear function (14). Therefore, the output of neural network controller can be rewritten as:

$$f(x) = W\phi(x) + \varepsilon(x) \quad (14)$$

Assumption 1: There exist unknown positive constants ε_{\max} and τ_{\max} such that $\|\varepsilon\| \leq \varepsilon_{\max}$ and $\|\tau\| \leq \tau_{\max}$

The torque control input is defined as:

$$\tau = \hat{f}(x) + \tau_r + \tau_p \quad (15)$$

$$\hat{f}(x) = \hat{W}\phi(x) \quad (16)$$

$$\tau_r = \hat{\rho} \frac{s}{\|s\|} \quad (17)$$

$$\tau_p = k_1 s \quad (18)$$

where $\hat{f}(x)$ is the estimate function of the nonlinear function $f(x)$, \hat{W} is estimate weight vector of W , τ_r is the adaptive robust control input, τ_p is the stabilizing control term, and k_1 is a constant denoted as the rate of error convergence.

Substituting (13) and (56) into (12), we obtain the closed-loop error dynamics for augment error s:

$$J\dot{s} = \tilde{W}\phi + \varepsilon - \tau_r - \tau_p + \tau_d \quad (19)$$

where $\tilde{W} = W - \hat{W}$ is the estimate weight error.

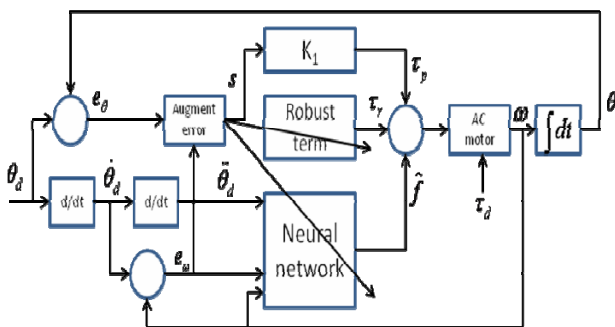


Fig. 2 Controller Scheme.

Consider the Lyapunov function:

$$V = \frac{1}{2} J s^2 + \frac{1}{2k_2} \tilde{W} \tilde{W}^T + \frac{1}{2k_3} \beta^2 \quad (20)$$

Differentiating (20) with respect to time and substituting (19) into the result, we can obtain:

$$\dot{V} = \tilde{W}^T (s\phi + \frac{1}{k_2} \tilde{W}) - k_1 s^2 - s\tau_r + s\varepsilon + s\tau_d + \frac{1}{k_3} \beta \dot{\beta} \quad (21)$$

By choosing the weight update rule:

$$\dot{\tilde{W}} = k_2 s \phi^T \quad (22)$$

and combining with Assumption 1, we can infer the boundedness of (21) as following:

$$\dot{V} \leq -k_1 s^2 + \|s\| \rho - \|s\| \hat{\rho} + \frac{1}{k_3} \beta \dot{\beta} \quad (23)$$

where $\rho = \varepsilon_{\max} + \tau_{d\max}$

Since $\beta = \rho - \hat{\rho}$ then

$$\dot{V} \leq -k_1 s^2 + \|s\| \beta + \frac{1}{k_3} \beta \dot{\beta} \quad (24)$$

The adaptation rule is simply selected as:

$$\dot{\beta} = k_3 \|s\| \quad (25)$$

It can be seen that the adaptation law (25) suppresses the approximation estimation error and disturbance, allows the augment error to converge to zero asymptotically:

$$\dot{V} \leq -k_1 s^2 \leq 0 \quad (26)$$

Because $s = e_{\omega} + \lambda e_{\theta}$ is stable dynamics, $e_{\theta} = \theta_d - \theta$ and $e_{\omega} = \omega_d - \omega$ are asymptotically stable.

In the next section, we present some simulations and experimental results to show the effectiveness of the proposed controller.

3. Simulation Results

Simulations are carried out by Matlab's Simulink to verify the asymptotic tracking performance of the proposed controller.

The simulation results of the proposed controller are illustrated in Fig.6, 7 and 8.

The reference angular position is denoted as a sine wave:

$$\theta_d = 2\pi \sin(2\pi t / 10) \quad (\text{rad})$$

The AC servo dynamic parameters in the simulation process are chosen as following:

$$J = 0.006 \text{kgm}^2, B = 0.0005 \text{kgm}^2 / \text{sec}$$

The neural network structure has 3 inputs, 5 neurons in hidden layer, and 1 output layer. The initial weights and thresholds are set as 0.01. The weights vector is updated online by the learning rule proposed in (16).

From the proof of stability, it can be seen that the constant k_1 determines the convergence speed of augment error s.

However, the bigger the k_1 is, the higher torque is needed to drive the system. The k_2 determines the learning speed of the neural network. Therefore, high gain k_2 can avoid the system uncertainties. The k_3 decides the adaptive speed of the robust term. Due to the characteristic of dynamics stability of augment error s , the constant λ should be chosen sufficiently small to guarantee the convergence of angular position error. In the simulation, the initial control gains and neural network structure are selected as:

$$k_1 = 100, k_2 = 5, k_3 = 100, \lambda = 0.01.$$

The moment of inertia J is increased 0.001 units every 2 seconds in the simulation as a presence of system uncertainty.

Disturbance τ_d is chosen as an impulse function with 10 Nm amplitude and 2 second period.

In the simulation, a conventional PID controller with fine tuning gains is presented to compare with the proposed controller.

From the simulation results, it can be seen that good tracking performance is achieved by using the proposed neural network learning rules.

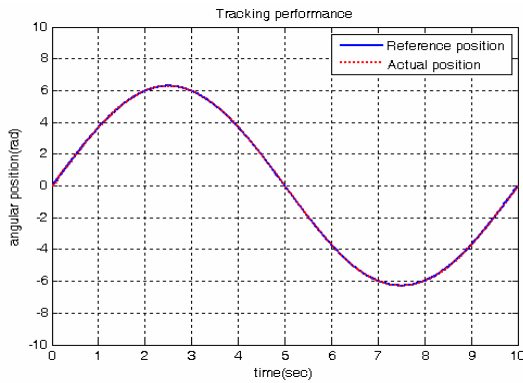


Fig. 3 Tracking performance of PID controller

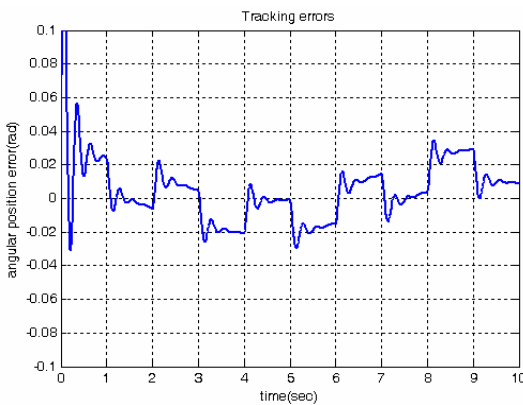


Fig. 4 Tracking error of PID controller

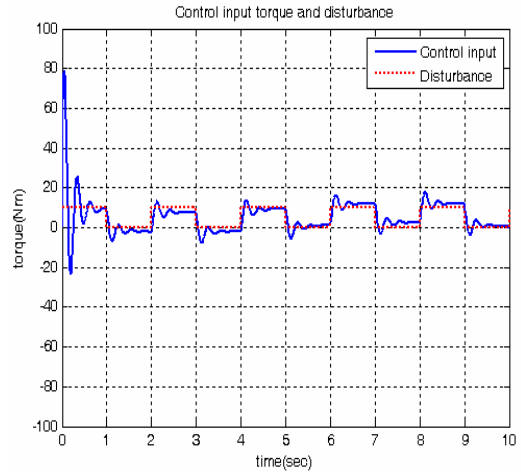


Fig. 5 Controller input torque and disturbance of PID controller

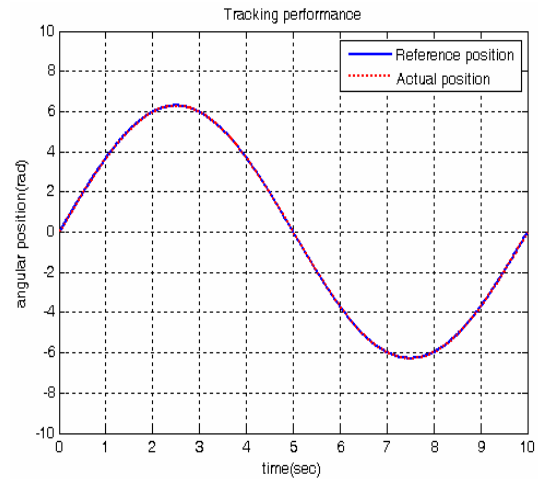


Fig. 6 Tracking performance of the proposed controller

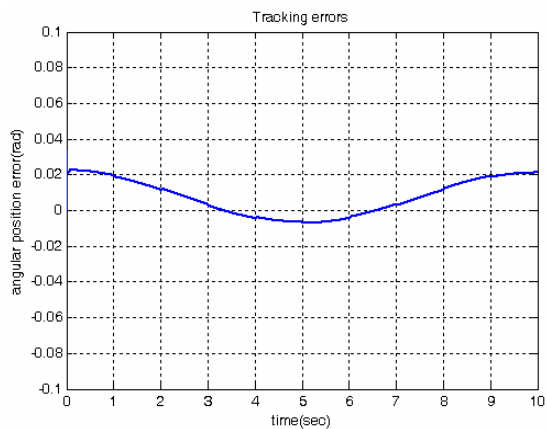


Fig. 7 Tracking error of the proposed controller

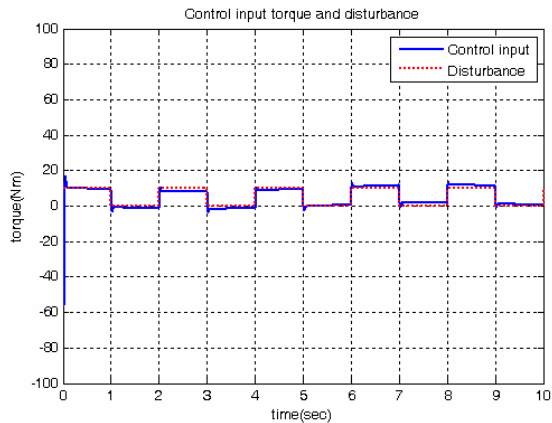


Fig. 8 Controller input torque and disturbance of the proposed controller

The simulation results from Fig.3, 4 and 5 show that the system with PID controller is sensitive to the disturbances and noises. Contrarily, the system with the proposed controller is robust as shown in Fig.6,7,8. Therefore, it is obvious that our proposed controller demonstrates superior tracking performance over the conventional PID controller.

4. Experimental Results

The motion control board consists of a DSP, a Universal Asynchronous Receiver/Transmitter, a CPLD, a 16-bit DAC, and some external memory chips. The proposed control algorithm is implemented in the floating-point DSP chip TMS320C6713-300 with the CPU clock rate of 300 MHz. The external interface clock rate is 50 MHz. The control sampling time is 500 micro seconds. The motion commands and data acquisition between computer and DSP board are performed through serial communication. The feedback position data from incremental encoder are carried out by the Xilinx CPLD XC95288XL.

The block diagram of a DSP based motion controller using the TMS320C6713 is shown in Fig.9.

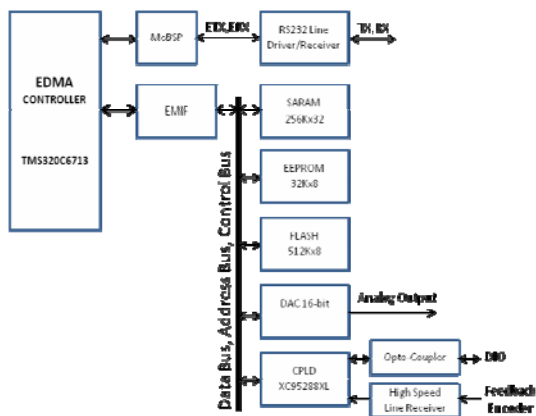


Fig. 9 Block diagram of DSP based motion controller



Fig. 10 Developed DSP based motion controller

The developed motion control system shown in Fig. 11 consists of a DSP-based motion controller, an analog amplifier, a LG FMA-CN02 servo motor, a linear stage RoboStar with 10mm lead screw, and a host computer. The AC servo motor, which has an encoder with a resolution of 2000 pulses/revolution, is driven by the ELMO analog amplifier.

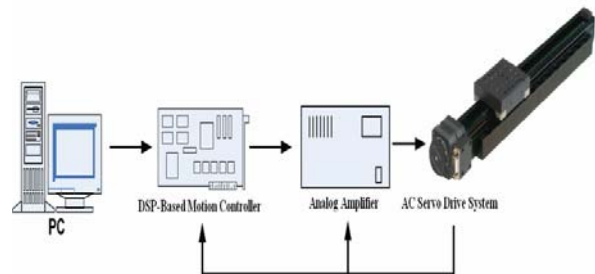


Fig. 11 Motion Control System

The experimental results using conventional PID controller and proposed controller are shown in Fig.12, Fig.13, Fig.16, Fig.17 and Fig.14, Fig.15, Fig.18, Fig.19 respectively.

In the experiment with PID controller, the control gains are chosen as: $K_p = 15$, $K_I = 200$, $K_D = 0.15$. For the proposed adaptive robust neural network controller, the convergence rate k_1 , the neural network learning rate k_2 , the adaptive speed k_3 , and the constant λ are selected as 120, 0.0005, 100, and 0.01 respectively. The initial weights and thresholds in neural network are set as 0.01.

The AC servo drive system is tested under sine wave and S-curve reference.

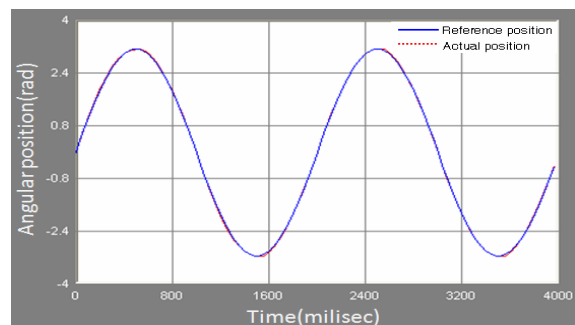


Fig. 12 Experimental tracking performance of PID controller due to sine wave reference

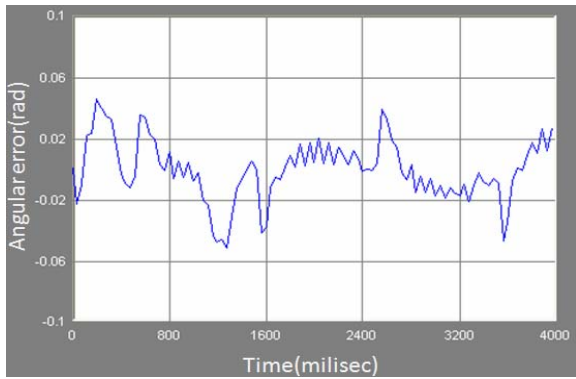


Fig. 13 Experimental tracking error of PID controller due to sine wave reference

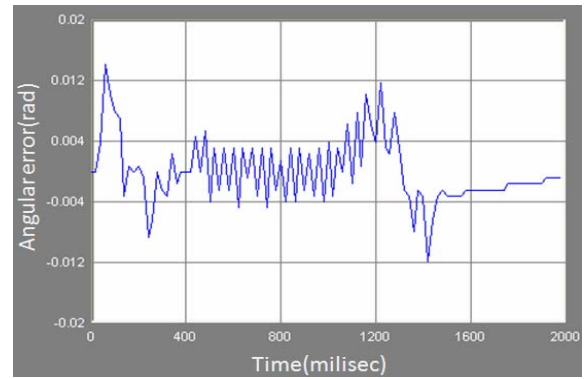


Fig. 17 Experimental tracking error of PID controller due to S-curve reference

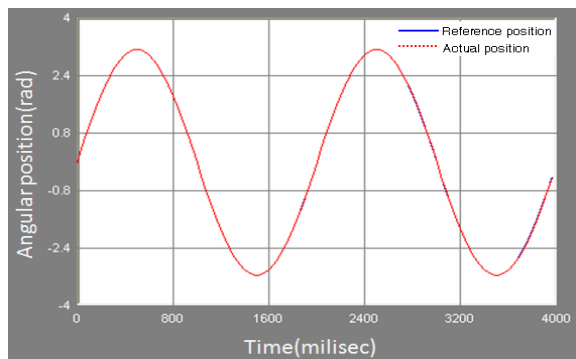


Fig. 14 Experimental tracking performance of proposed controller due to sine wave reference

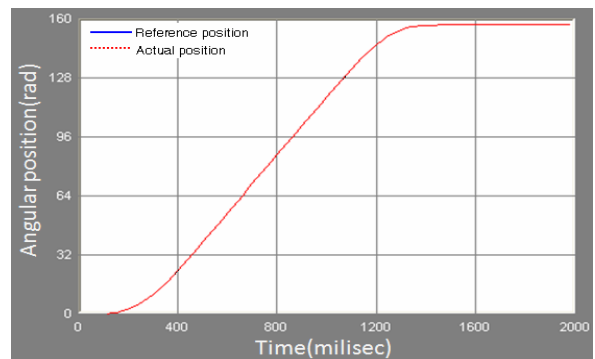


Fig. 18 Experimental tracking performance of proposed controller due to S-curve reference

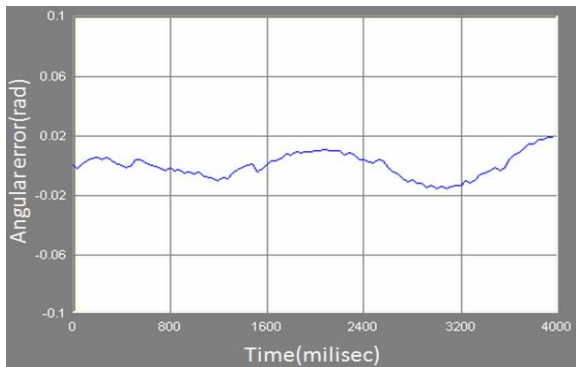


Fig. 15 Experimental tracking error of proposed controller due to sine wave reference

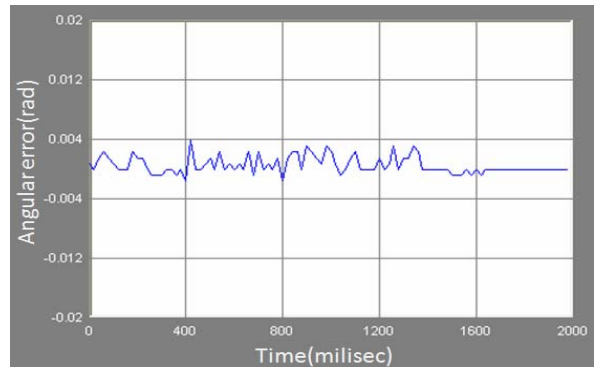


Fig. 19 Experimental tracking error of proposed controller due to S-curve reference

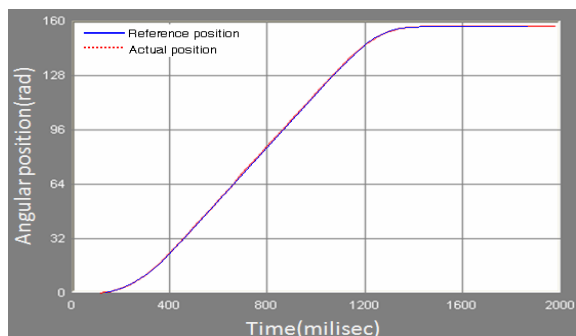


Fig. 16 Experimental tracking performance of PID controller due to S-curve reference

From the experimental results, it can be seen that by using the proposed controller, the rotor angle follows its desired trajectory satisfactorily, and the position error of the experiment is as small as that of the simulation results.

5. Conclusions

In this paper, an adaptive robust neural network is presented to perform high precise motion tracking for AC servo drives. Fast learning rule of the neural network and stable adaptive mechanism enable the controller to overcome system

uncertainties and external disturbances.

From the simulation and experimental results, we have confirmed that the effectiveness and validity of the proposed adaptive robust neural scheme was successful in maintaining precise and stable performance of the motion control system. Hence, this controller is applicable in high precision closed-loop motion control system for a CNC machine, a planning machine, a robot control, and etc..

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Won-Ho Kim

received the B.S., M.S. and Ph.D. degree in School of Electronics Engineering from Kyungpook National University, Daegu, Korea, in 1985, 1988 and 1999, respectively. From 1988 to 1993, he was a researcher of Electronics & Telecommunications Research Institute (ETRI). He is currently an associate professor in the Department of Mechatronics Engineering, Dong-Eui University, Busan, Korea. His research interests include robotics and embedded control systems.