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Robust Adaptive Back-stepping Control Using Dual Friction Observer and RNN with Disturbance Observer for Dynamic Friction Model

Seong Ik Han*

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외란관측기를 갖는 RNN과 이중마찰관측기를 이용한 동적마찰모델에 대한 강인한 적응 백-스테핑제어

한성익*

Abstract

For precise tracking control of a servo system with nonlinear friction, a robust friction compensation scheme is presented in this paper. The nonlinear friction is difficult to identify the friction parameters exactly through experiments. Friction parameters can be also varied according to contact conditions such as the variation of temperature and lubrication. Thus, in order to overcome these problems and obtain the desired position tracking performance, a robust adaptive back-stepping control scheme with a dual friction observer is developed. In addition, to estimate lumped friction uncertainty due to modeling errors, a DEKF recurrent neural network and adaptive reconstructed error estimator are also developed. The feasibility of the proposed control scheme is verified through the experiment for a ball-screw system.

Key Words : LuGre friction model(LuGre 마찰모델), Adaptive back-stepping control(적응형 백스테핑제어), Dual friction observer (이중마찰관측기), Recurrent neural network(순환형 신경망), Adaptive reconstructed error estimator(적응형 재설정 오차추정기), Decoupled extended Kalman filter(비연성 확장칼만필터), Ball-screw systems(볼-스크류 시스템)

1. Introduction

Friction is a phenomenon that almost appears in mechanical systems contacted each other. It affects the tracking performance of servo systems such as machine tools and robots. In the moderate velocity range, in

* Dept. of Electrical Automation, Suncheon First College (hansng@suncheon.ac.kr)
Address: 9-3 Dukwoldong, Suncheon, Chennam, 540-744, Korea

general, a classical friction model is used which consists of the Coulomb and viscous friction The classical friction model can consider only static characteristics of the friction force and velocity. The classical friction model, therefore, fails to capture the low velocity effects such as the Stribeck effect, stick-slip motion, pre-sliding motion, and break-away force, which play a significant role in high precise position tracking applications. Besides these friction effects, through many researches, it has been revealed that friction is also influenced by the factors such as interior temperature of friction surface, contacting time, magnitude of load, and operating distance.

The dynamic friction, called LuGre friction model(1), provides the sufficient acceptable property of the dynamic friction and its simple structures, most researchers has adopted this model as a standard friction model. However, the LuGre model has a drawback that cannot exactly describe the friction dynamics in the pre-sliding range where the hysteresis phenomena appear(2,3). In spite of the inability of the exact description for hysteresis friction of this models, several researches(4~7) have adopted to control the friction system as the LuGre model since it almost satisfy the most part of the nonlinear friction characteristic and is easier to analyze and implement than other second-order friction models.

In general, the control methods for the compensation of nonlinear friction are divided into two types. One is the friction model-based method and the other is the non-friction model-based method without friction observer. The latter approach is mainly used when the exact friction model cannot be constructed and precise tracking performance is not required. In the low precision level, this approach can be applied conveniently because the procedure of the friction parameter identification can be omitted and the structure of the controller is simple. The neural network control(8) and sliding mode control(9) belong to the non-model based method. The model-based method can be applied when the identification for friction model is possible within a certain exact range of precision level. It can obtain more precise tracking performance but cannot avoid a little complexity of control system and difficulty of the exact identification of friction parameters. PID/friction observer-based control method(10~12) and adaptive control method(13) belong to the model-based method. A recurrent neural networks (RNN)(14,15) for the approximation of unknown function have been developed recently by many people since it provides a dynamic mapping and demonstrates good control approximation performance compared with a static neural networks such as feedforward neural networks which needs a large number of neuron to represent dynamic response. A RNN using extended Kalman filter was also developed by several authors (16,17) since it gives the computational merits and more optimal learning algorithms than a similar RNN.

In this paper, in order to estimate the friction parameters and uncertainty friction torque, a robust adaptive back-stepping scheme using dual friction observer and RNN with reconstructed error estimator is proposed. In order to show the feasibility of the proposed control scheme, some experiments for a ball-screw system with the non-linear dynamic friction are carried out.

2. LuGre fricton model

The LuGre friction model(1) as shown in Fig. 1 is described as

$$\dot{z} = \dot{q} - \sigma_0 h(\dot{q}) z \tag{1}$$

$$T_f = \alpha_0 z + \alpha_1 \dot{z} + \alpha_2 \dot{q} \tag{2}$$

where

$$h(\dot{q}) = \frac{|\dot{q}|}{g(\dot{q})} \tag{3}$$

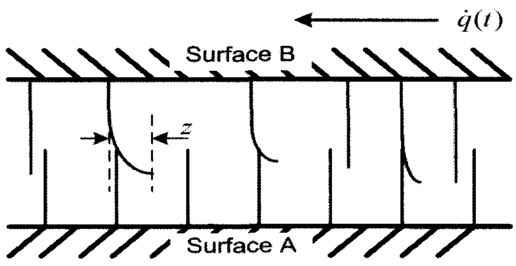

Fig. 1 The friction interfaces with bristles between two surfaces

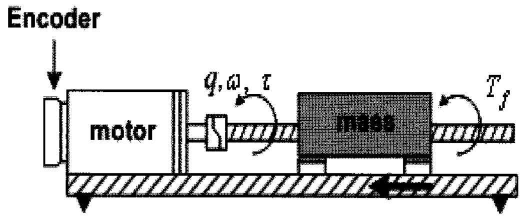

Fig. 2 Layout of the ball-screw system

$$g(\dot{q}) = T_c + (T_s - T_c)e^{-(\dot{q}/q_s)^2} \tag{4}$$

where q is generalized position, σ_0 is nominal static friction parameter, and α_0, α_1, α_2 are friction parameters that can be explained as stiffness of bristles, damping coefficient, and viscous damping coefficient. $\dot{q}_s$ is the Stibeck velocity, T_s is static friction torque, T_c is Coulomb friction coefficient. The function $g(\bullet)$ is assumed to be known and positive and depends on many factors such as material properties and temperature. In order to consider the variation of friction torque, T_f, it is assumed that the coefficients, α_0, α_1, α_2 are independent unknown positive constants. As shown in Fig. 2, the motion equation for a ball-screw system can be represented as follows:

$$J\ddot{q} = u_p - T_f - T_d \tag{5}$$

where u_p is the control input torque, T_d is a lumped model uncertainty, which contains the friction modeling error, and J is the moment of inertia of the ball-screw and DC motor. Introducing Eq. (1) and (2) into Eq. (5), Eq. (5) can be written as follows:

$$J\ddot{q} = u_p - (\alpha_0 z - \alpha_3 h(\dot{q})z + \alpha_4\dot{q}) - T_d \tag{6}$$

where $\alpha_3 = \sigma_0\alpha_1$, $\alpha_4 = \alpha_1 + \alpha_2$.

3. Design of the controller and observer

The control objective is to design an adaptive back-stepping control system for the output q of the system to track the desired position q_d asymptotically. A proposed adaptive back-stepping control system is designed step by step as follows.

Step 1. For the tracking objective, define the following position tracking error

$$y_1 = q - q_d \tag{7}$$

and its time derivative is

$$\dot{y}_1 = \dot{q} - \dot{q}_d \tag{8}$$

Define the following stabilizing function

$$\alpha_1 = \dot{q}_d - k_1 y_1 \tag{9}$$

where k_1 is a positive constant. Define the following Lyapunov function

$$V_1 = \frac{1}{2}y_1^2 \tag{10}$$

Define $y_2 = \dot{q} - \alpha_1$, then the time derivative of V_1 is

$$\begin{aligned}\dot{V}_1 &= y_1\dot{y}_1 = y_1(\dot{q} - \dot{q}_d) = y_1(\dot{q} - \alpha_1 - k_1 y_1)\\ &= y_1 y_2 - k_1 y_1^2\end{aligned} \tag{11}$$

Step 2. The time derivative of y_2 is

$$\begin{aligned}\dot{y}_2 &= \ddot{q} - \dot{\alpha}_1\\ &= \frac{u_p}{J} - \frac{1}{J}(\alpha_0 z - \alpha_3 h(\dot{q})z + \alpha_4\dot{q}) - \frac{T_d}{J} - \dot{\alpha}_1\end{aligned} \tag{12}$$

Now, we introduce the following the dual-observer[7] for estimating immeasurable friction state z

$$\dot{\hat{z}}_0 = \dot{q} - \sigma_0 h(\dot{q})\hat{z}_0 + \eta_0 \tag{13}$$

$$\dot{\hat{z}}_1 = \dot{q} - \sigma_0 h(\dot{q})\hat{z}_1 + \eta_1 \tag{14}$$

where $\hat{z}_0$, $\hat{z}_1$ are estimates for the friction state z and η_0, η_1 are observer dynamic terms that are to be designed. The corresponding observation errors are given as follows:

$$\dot{\tilde{z}}_0 = -\sigma_0 h(\dot{q})\tilde{z}_0 - \eta_0 \tag{15}$$

$$\dot{\tilde{z}}_1 = -\sigma_0 h(\dot{q})\tilde{z}_1 - \eta_1 \tag{16}$$

Next, define the following Lyapunov function

$$V_2 = V_1 + \frac{1}{2} y_2^2 \tag{17}$$

The time derivative of V_2 can be induced by the above results

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + y_2 \dot{y}_2 \\ &= -k_1 y_1^2 + y_2 [y_1 - \frac{1}{J}(\alpha_0 z - \alpha_3 h(\dot{q}) z + \alpha_4 \dot{q}) \\ &\quad + \frac{u_p}{J} - \frac{T_d}{J} - \dot{\alpha}_1] \end{aligned} \tag{18}$$

In a practical application, since it is difficult to determine the lumped uncertainty T_d previously, a RNN approximator using the DEKF algorithm[18] is introduced to estimate the value of $\hat{T}_d$. DEKF parameters are computed as follows:

$$\boldsymbol{\Gamma}(n) = \left[\sum_{k=1}^{g} \boldsymbol{C}_{mk}(n) \boldsymbol{K}_k(n, n-1) \boldsymbol{C}_k^T(n) + \boldsymbol{R}(n) \right]^{-1} \tag{19}$$

$$\boldsymbol{G}_k(n) = \boldsymbol{K}_k(n, n-1) \boldsymbol{C}_{mk}^T(n) \boldsymbol{\Gamma}(n) \tag{20}$$

$$\phi(n) = \boldsymbol{d}(n) - \hat{\boldsymbol{d}}(n/n-1) \tag{21}$$

$$\hat{\boldsymbol{w}}_k(n+1/n) = \hat{\boldsymbol{w}}_k(n/n-1) + \boldsymbol{G}_k(n)\phi(n) \tag{22}$$

$$\begin{aligned} \boldsymbol{K}_k(n+1, n) &= \boldsymbol{K}_k(n, n-1) - \boldsymbol{G}_k(n) \boldsymbol{C}_{mk}(n) \boldsymbol{K}_k(n, n-1) \\ &\quad + \boldsymbol{Q}_k(n) \end{aligned} \tag{23}$$

where Γ_n is a p-by-p matrix, p denoting the number of outputs. $G_k(n)$ is W_k-by-p matrix denoting the Kalman gain for group k, where W_k stands for the number of weights in group g. $\Phi(n)$ is a p-by-1 vector, denoting the innovations defined as the difference between the desired response $\boldsymbol{d}(n)$ for the linearized system and its estimated

$$\hat{\boldsymbol{d}}(n/n-1) = \boldsymbol{C}_{mk}(n) \hat{\boldsymbol{w}}_k(n/n-1) \tag{24}$$

where $\widehat{w}_k(n/n-1)$ is a W_k-by-1 vector, denoting the estimate of the weight vector $\widehat{w}_k(n)$ for group k at time n given the observed data up time n-1. $K_k(n, n-1)$ is a W_k-by- W_k matrix, denoting the error covariance matrix for group k. It is initialized as $K_k(1,0) = \epsilon^{-1} I$ where ϵ is a small positive constant. The initial weights are small values selected from a uniform distribution. At each time instant, an input pattern is applied to the network, and the partial derivatives of the output with respect to all the weights in the network are computed to derive the linearized measurement matrix, and EKF equations are applied. All the computations are made real time, and there is no need for history buffer to save the past values of weights. Only elements to be saved are the hidden neuron outputs which play the role of inputs at the next time instant.

Fig. 3 shows the network structure used in this paper. Weight matrix $\boldsymbol{w}$ represents the weights leading to the first hidden unit. It consists of the connections coming from the past values of hidden unit outputs, input node, and bias. The past output values of hidden units are included in vector:

$$\boldsymbol{x}(n) = [x_1(n)\ x_2(n) \ldots\ x_q(n)] \tag{25}$$

Weight vector w_a holds the weights between two hidden layers, and w_b represents the weights leading to linear output node. x_b is the vector of the outputs of second hidden layer units. Rewriting Eq. (24), the output of the RNN is

$$\hat{T}_d = \boldsymbol{C}_m^T \boldsymbol{W}_{all} \tag{26}$$

where $C_m = [C_1\ C_2\ \ldots\ C_q]^T$, q is the number of the layer and $W_{all} = [w, w_a, w_b]^T$. Then, since exact RNN approximation to lumped uncertainty can be impossible, define

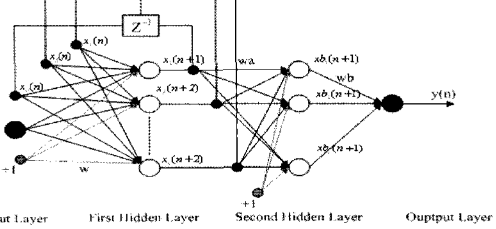

Fig. 3 Recurrent multilayer perceptron with two hidden layer

the following reconstructed error E

$$E = T_d - \hat{T}_d \tag{27}$$

where it is assumed that $|E| \le \overline{E}$ and $\overline{E}$ is the upper bound of E, and E is assumed to be constant in during adaptation.

$$V_3 = V_2 + \frac{1}{2\rho}(\hat{E} - E)^2 \tag{28}$$

where ρ is a positive constant. $\hat{E}$ is the estimated value of the reconstruction error. The time derivative of Eq. (28) can be written as

$$\begin{aligned} \dot{V}_3 &= \dot{V}_2 + \frac{1}{\rho}(\hat{E} - E)\dot{\hat{E}} \\ &= -k_1 y_1^2 + y_2[y_1 - \frac{1}{J}(\alpha_0 z - \alpha_3 h(\dot{q}) z + \alpha_4 \dot{q}) \\ &\quad + \frac{u_p}{J} - \frac{T_d}{J} - \dot{\alpha}_1] + \frac{1}{\rho}(\hat{E} - E)\dot{\hat{E}} \end{aligned} \tag{29}$$

From Eq. (29), an adaptive back-stepping control law is chosen as follows:

$$\begin{aligned} u_p &= J[-y_1 - k_2 y_2 + \dot{\alpha}_1] \\ &\quad + \hat{\alpha}_0 \hat{z}_0 - \hat{\alpha}_3 h(\dot{q}) \hat{z}_1 + \hat{\alpha}_4 \dot{q} + \hat{T}_d + \hat{E} \end{aligned} \tag{30}$$

where k_2 is a positive constant. Introducing Eq. (30) into Eq. (29), then

$$\begin{aligned} \dot{V}_3 &= -k_1 y_1^2 - k_2 y_2^2 + y_2[-\frac{1}{J}(\alpha_0 \tilde{z}_0 + \tilde{\alpha}_0 \hat{z}_0 \\ &\quad -\alpha_3 h(\dot{q}) \tilde{z}_1 - \tilde{\alpha}_3 h(\dot{q}) \hat{z}_1 + \tilde{\alpha}_4 \dot{q}) \\ &\quad + \frac{\hat{T}_d}{J} - \frac{T_d}{J} + \frac{\hat{E}}{J}] + \frac{1}{\rho}(\hat{E} - E)\dot{\hat{E}} \end{aligned} \tag{31}$$

where $\tilde{\alpha}_0 = \alpha_0 - \hat{\alpha}_0$, $\tilde{\alpha}_3 = \alpha_3 - \hat{\alpha}_3$ and $\tilde{\alpha}_4 = \alpha_4 - \hat{\alpha}_4$ are unknown parameter estimate errors. Now, define the following Lyapunov function

$$\begin{aligned} V_4 &= V_3 + \frac{1}{2}\alpha_0 \tilde{z}_0^2 + \frac{1}{2}\alpha_3 \tilde{z}_1^2 + \frac{1}{2\gamma_0}\tilde{\alpha}_0^2 \\ &\quad + \frac{1}{2\gamma_3}\tilde{\alpha}_3^2 + \frac{1}{2\gamma_4}\tilde{\alpha}_4^2 \end{aligned} \tag{32}$$

The time derivative of V_4 can be obtained as

$$\begin{aligned} \dot{V}_4 &= -k_1 y_1^2 - k_2 y_2^2 - \alpha_0 \sigma_0 h(\dot{q}) \tilde{z}_0^2 - \alpha_3 \sigma_0 h(\dot{q}) \tilde{z}_1^2 \\ &\quad + \tilde{\alpha}_0(-\frac{y_2}{J}\hat{z}_0 - \frac{1}{\gamma_0}\dot{\hat{\alpha}}_0) + \tilde{\alpha}_3(\frac{y_2 h(\dot{q})}{J}\hat{z}_1 - \frac{1}{\gamma_3}\dot{\hat{\alpha}}_3) \\ &\quad + \tilde{\alpha}_4(-\frac{y_2}{J}\dot{q} - \frac{1}{\gamma_4}\dot{\hat{\alpha}}_4) + \tilde{z}_0(-\alpha_0 \frac{y_2}{J} - \alpha_0 \eta_0) \\ &\quad + \tilde{z}_1(\alpha_3 \frac{y_2}{J} h(\dot{q}) - \alpha_3 \eta_1) + (\hat{E} - E)(\frac{y_2}{J} + \frac{1}{\rho}\dot{\hat{E}}) \end{aligned} \tag{33}$$

The update laws for the parameter estimates can be determined as follows:

$$\dot{\hat{\alpha}}_0 = -\frac{\gamma_0}{J} y_2 \hat{z}_0 \tag{34}$$

$$\dot{\hat{\alpha}}_3 = \frac{\gamma_3}{J} y_2 h(\dot{q}) \hat{z}_1 \tag{35}$$

$$\dot{\hat{\alpha}}_4 = -\frac{\gamma_4}{J} \dot{q} y_2 \tag{36}$$

and the observer dynamic terms are obtained by

$$\eta_0 = -\frac{y_2}{J} \tag{37}$$

$$\eta_1 = \frac{y_2}{J} h(\dot{q}) \tag{38}$$

In Eq. (33), the adaptation law for $\dot{\hat{E}}$ of the reconstructed error can be chosen as follows:

$$\dot{\hat{E}} = -\rho \frac{y_2}{J} \tag{39}$$

With the above choices for the update laws and the observer dynamic terms, the Lyapunov derivative in Eq. (33) becomes

$$\begin{aligned} \dot{V}_4 &= -k_1 y_1^2 - k_2 y_2^2 - \frac{\alpha_0 \sigma_0}{J} h(\dot{q}) \tilde{z}_0^2 - \frac{\alpha_3 \sigma_0 h(\dot{q})}{J} \tilde{z}_1^2 \\ &\le -k_1 y_1^2 - k_2 y_2^2 \le 0 \end{aligned} \tag{40}$$

From the above equation, define $W(y(\tau))$

$$W(y(\tau)) = k_1 y_1^2 + k_2 y_2^2 \le -\dot{V}_4(y_1, y_2) \tag{41}$$

Since $\dot{V}_4 \le 0$, V_4 is nonincreasing. Thus, it has a limit

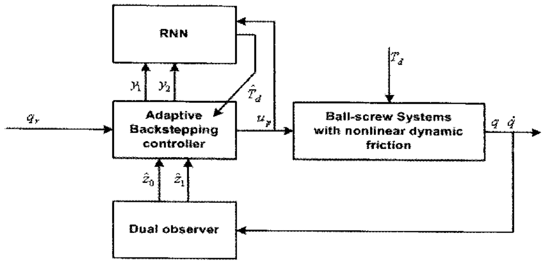

Fig. 4 The proposed adaptive back-stepping control system using the RNN and disturbance observer

$V_{4\infty}$ as $t \to \infty$. Integrating Eq. (41), then

$$\lim_{t\to\infty} \int_0^t W(y(\tau))d\tau \le -\lim_{t\to\infty} \int_0^t \dot{V}_4(y_1, y_2)d\tau$$
$$= \lim_{t\to\infty} \{V_4(y(t_0), t_0) - V_4(y(t), t)\}$$
$$= V_4(y(t_0), t_0) - V_{4\infty} \quad (42)$$

which means that $\int_{t_0}^{t} W(y(\tau))d\tau$ exits and finite. Since $W(y(t))$ is also uniformly continuous, the following result can be obtained from Barbalat lemma[19].

$$\lim_{t\to\infty} W(y(t)) = 0 \quad (43)$$

Since y_1 and y_2 converge to zero as $t \to \infty$, q and $\dot{q}$ approach q_d and $\dot{q}_d$ as $t \to \infty$. Finally, the back-stepping control system is asymptotically stable in spite of the variation of the system parameters and external disturbance. Fig. 4 represents the proposed adaptive back-stepping control system using the RNN and disturbance observer.

4. Experiment and discussion

The experiment is executed for the verification of the precision tracking control of a ball-screw system with nonlinear dynamic friction. The system components and parameters are given in Table 1 and 2. Three control schemes are designed to compare with the proposed control scheme: an adaptive back-stepping control system (AB system), adaptive back-stepping control system with a dual observer (ABFO system), and adaptive back-stepping control system with a dual observer, RNN and reconstructed error estimator (ABFORO system).

Table 1 Parameters of ball-screw and friction model

Symbol	Value
J	0.246 kgm^2
T_c	0.088 Nm
T_s	0.11 Nm
$\dot{q}_s$	0.056 rad/sec
σ_0	86.4 Nm/rad
σ_1	4.7 Nmsec/rad
torque constant	0.3 Nm/A
amplifier gain	2.72 A/V

Table 2 Specification of system components of the control system

Item	Specification
IBM PC	Pentium II, MS-DOS, C-language
Data Acquisition board	DR8330, DA resolution : 12 bits
Encoder counter board	PCL-833Resolution : 32bits
Motor driver	FDD-106PD
DC servo motor	300W, 3000rpm
Encoder	ITD 21 B14, resolution 10000 pulse/rev
Ball-screw	THK, C0 grade

The control algorithms are programmed in C code and the control signals are transmitted into the DC motor drive through the DR8330 data acquisition board. The radian position of the ball-screw system is obtained by the precise encoder coupled with the DC motor shaft. Fig. 5 shows the command position input and output for AB system. From Fig. 5, it can be shown that the position tracking performance is very poor since the friction disturbs the position performance. Fig. 6 shows

the command position input and output of the ABFO system where the tracking performances are improved significantly than that of AB system. The reason is that the friction observer compensates the friction torque

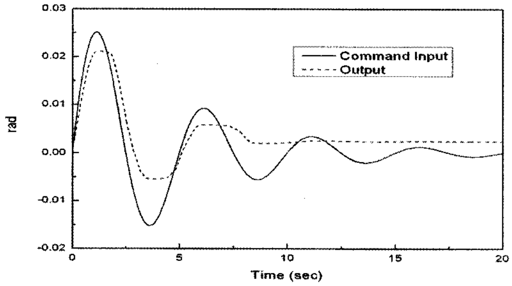

Fig. 5 Command position input and output of the AB system

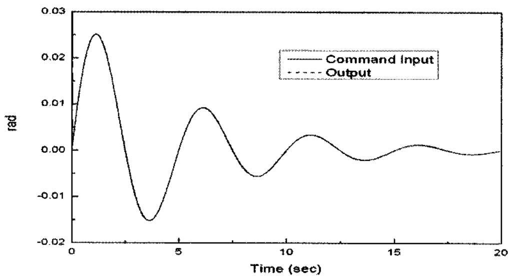

Fig. 6 Command position input and output of the ABFO system

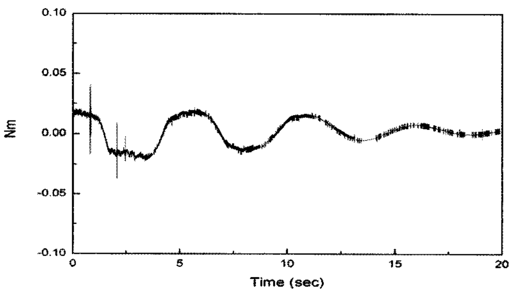

Fig. 7 Control input of the ABFO system

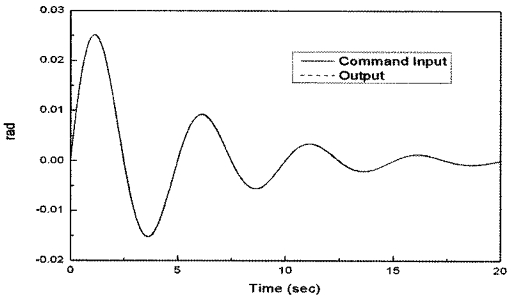

Fig. 8 Command position input and output of the ABFORO system

variations in low level ranges. Thus, it can be known that the friction observer acts an important role to improve the tracking performances. Fig. 7 shows the control input for the command position input given in Fig. 6. Fig. 8 and 9 show the command position input and output and control input of the ABFORO control system where the tracking performances are also much improved similar to the ABFO system, but the precise performance is superior

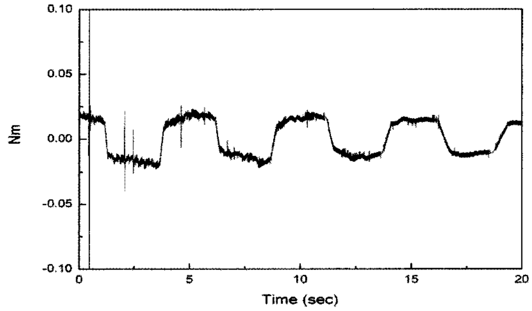

Fig. 9 Control input of the ABFORO system

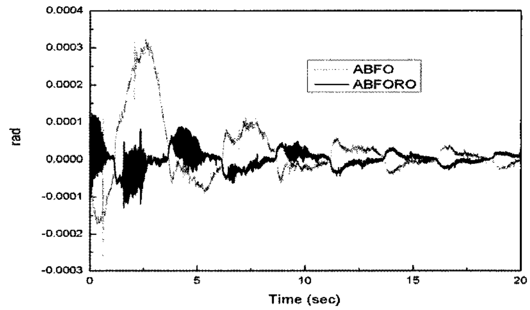

Fig. 10 Tracking errors of the ABFO and ABFORO system

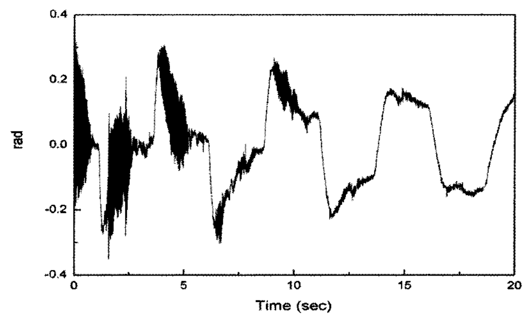

Fig. 11 The estimated value of the friction state z_0

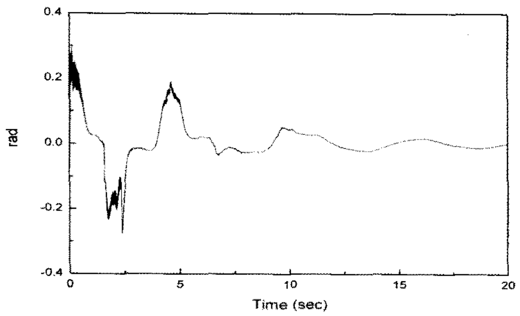

Fig. 12 The estimated value of the friction state z_1

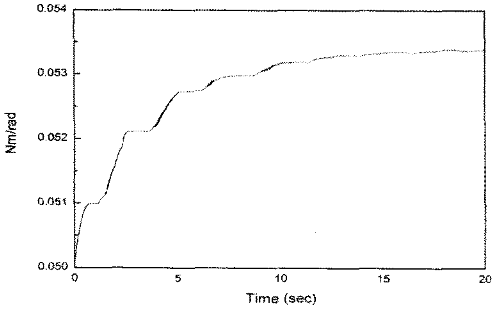

Fig. 13 The estimated value of the friction parameter $\hat{\alpha}_0$

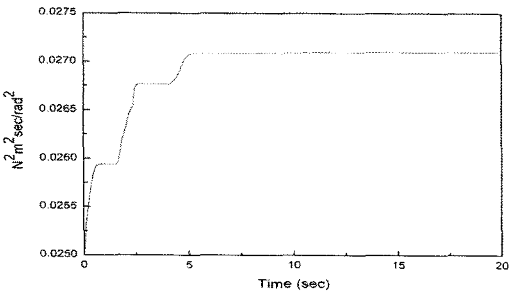

Fig. 14 The estimated value of the friction parameter $\hat{\alpha}_3$

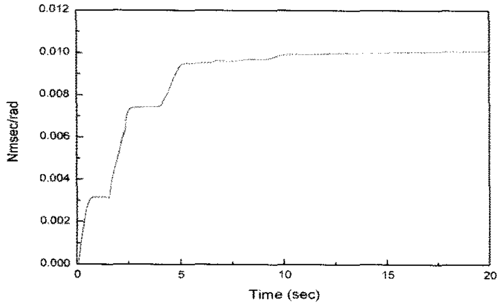

Fig. 15 The estimated value of the friction parameter $\hat{\alpha}_4$

than the ABFO control system as shown in Fig. 10 since the RNN and error estimator compensate the unmodeled friction parameters of the friction model acting the uncertainty of the system. From Fig. 11 to Fig. 15, the estimated friction parameters are presented where each estimated parameter is converged in certain values.

5. Conclusion

In this paper, the robust adaptive control scheme to the dynamic friction system is proposed to compensate the friction torque and uncertainty using the back-stepping control, dual friction observer and RNN method. Some experiments on the ball-screw system show that the proposed friction compensation scheme gives good tracking performance compared with the back-stepping control and only friction observer compensation case. The unmodeled uncertainty can be effectively compensated by the RNN and error estimator. Thus, it is shown that the proposed control system can provide the robustness of the servo system with nonlinear friction. The proposed control scheme can be also applied to the precise mechanical system such as the electro mechanical actuator (EMA), the electro hydraulic actuator (EHA) and machine tools, etc.

As the next researches, a robust control using other RNN methods and recurrent fuzzy neural network will be developed in a near time.

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