Research Article

Adaptive Neuron-Like Control of Time-Delay Systems Enhanced with Feedforward and Supervisory Strategies

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Tracking control of nonlinear systems with significant delay effects has been the focus of intensive research. In this paper, we propose an effective supervised adaptive control scheme to tackle the problem. The scheme is composed of an adaptive control part of two neuron-like models with delay effects and a supervisory control part to enhance robustness against disturbance and model uncertainties. A design methodology based on the Lyapunov analysis is presented. Experimental results obtained from a practical temperature control system show that not only is the design procedure conceptually simple but also the control performance is also excellent when compared with the traditional PD controller. Also, the feedforward term is able to provide extra improvement in the regulation performance.

1. Introduction

The study of stability and stabilization for time-delay systems has received considerable attention in recent years [1–4] since delay is a major source of instability in many important engineering systems [5, 6]. For instance, Hopf bifurcation caused by time delay is extensively investigated in [7–10].

The applicability of neural-network-based techniques in nonlinear control systems has been successively demonstrated in [11–13] because of their unique modeling capability and adaptability [14, 15]. However, delay effects are not effectively considered in most of the proposed schemes and modeling error is ignored, which may be a potential source of instability [16]. As neural networks have superior capability in the construction of models of complex nonlinear systems, [17–20] use a feed-forward neural network for model-based predictive control. However, only simulation results are demonstrated in most of these researches. Reference [21] also applied an indirectly derived feedforward term in a simulation study, but the approach is based on predictability of disturbances.

In this paper, a particular class of adaptive neural controller is proposed based on a time-delay neural model.

Inspired by [22], the model-based adaptation law has two auto-tuning neurons in which both delay effects and feedforward terms are explicitly included, which are not considered in the original contribution. Robustness and stability conditions are derived in the sense of Lyapunov for the design of the proposed adaptation scheme, and performance of the proposed scheme is demonstrated by experimental results of a temperature control system.

2. Problem Formulation

The plant under control is assumed to be nonlinear with system dynamics being represented as

$$\dot{x}^{(n)}(t) = f(X, X_d, w_m(t, \tau)) + g(X)u(t) + d_0(t), \quad (1)$$

where $u(t)$ is the control input, d_0 is unknown but bounded disturbance with $|d_0(t)| \leq d_U$, and $w_m(t, \tau)$ is measurable or predictable disturbance with delay τ . Furthermore, $X = [\xi(t), \dot{\xi}(t), \dots, \xi^{(n-1)}(t)]^T = [x_1(t), x_2(t), \dots, x_n(t)]^T \in \mathfrak{R}^{n \times 1}$ is the state vector of the nonlinear system with $x(t)$ being the state of the system and $x_i(t)$, $i = 1 \sim n$ being its derivatives, and $X_d = [\xi(t - \tau_d), \dot{\xi}(t - \tau_d), \dots, \xi^{(n-1)}(t - \tau_d)]^T = [x_1(t - \tau_d),$

$x_2(t - \tau_d), \dots, x_n(t - \tau_d)]^T$ is the delayed state vector with delay τ_d ; $f(\cdot)$ is the nonlinear system function in X , X_d , and w_m . Note that the nonlinear input gain $g(\cdot)$ is assumed to be a function in X only.

3. Controller Design

Firstly, we define the desired output as y_r and tracking error as $e = y_r - \xi$. Then we may define $Y_r = [y_r, \dot{y}_r, \dots, y_r^{(n-1)}]^T$ and $E = [e, \dot{e}, \dots, e^{(n-1)}]^T$. Suppose that we choose a gain vector $K = [k_0, k_1, \dots, k_{n-1}]^T$ such that all roots of $s^n + k_{n-1}s^{n-1} + \dots + k_1s + k_0 = 0$ are in the open left-half complex plane. The proposed control law $u(t)$ is given by

$$u(t) = u_C(\theta_f, \theta_g) + u_S, \quad (2)$$

where $u_C(\theta_f, \theta_g)$ is an adaptive control law and u_S is a supervisory control law which enhances the robustness of the closed-loop system and improves transient performance by keeping system states stay in some prespecified region. The adaptive control law is defined as

$$u_C(\theta_f, \theta_g) = \hat{g}^{-1}(\theta_g) [-\hat{f}(\theta_f) + y_r^{(n)} + K^T E], \quad (3)$$

where $\hat{f}(\theta_f)$ and $\hat{g}(\theta_g)$ are two neuron-like models:

$$\begin{aligned} \hat{g}(\theta_g) &= \frac{2a_g}{1 + \exp(-b_g \cdot [-h_g + \sum_{i=1}^n \mu_i x_i(t)])}, \quad (4) \\ \hat{f}(\theta_f) &= \left(a_f \cdot \left\{ 1 - \exp \right. \right. \\ &\quad \times \left(-b_f \cdot \left\{ h_f + \sum_{j=0}^J \sum_{i=1}^n [\mu_{ij} x_i(t - j \cdot \tau)] \right. \right. \\ &\quad \left. \left. + \sum_{l=0}^L K_{Fl} w_m(t - l \cdot \tau) \right\} \right) \left. \right\} \left. \right) \\ &\quad \times \left(1 + \exp \right. \\ &\quad \times \left(-b_f \cdot \left\{ h_f + \sum_{j=0}^J \sum_{i=1}^n [\mu_{ij} x_i(t - j \cdot \tau)] \right. \right. \\ &\quad \left. \left. + \sum_{l=0}^L K_{Fl} w_m(t - l \cdot \tau) \right\} \right) \left. \right\} \left. \right)^{-1}, \end{aligned} \quad (5)$$

where $\theta_f = [a_f, b_f, h_f, K_{F0}, K_{F1}, \dots, K_{FL}, \mu_{10}, \mu_{20}, \dots]^T$ and $\theta_g = [a_g, b_g, h_g, \mu_1, \mu_2, \dots]^T$, with a_g , b_g , and h_g being positive, are adjustable parameters, $w_m(t)$ is a feed-forward term, and $K_{F0}, K_{F1}, \dots, K_{FL}$ are the corresponding feed-forward

gains. In this study, two adaptation laws with projection mapping are defined as follows:

$$\dot{\theta}_f = \begin{cases} \varphi_f, & \text{if } (\|\theta_f\| < M_f) \\ \text{or } (\|\theta_f\| = M_f, -\theta_f^T \varphi_f \geq 0), \\ \varphi_f - \frac{\theta_f}{\|\theta_f\|^2} \theta_f^T \varphi_f, & \text{otherwise,} \end{cases} \quad (6)$$

$$\dot{\theta}_g = \begin{cases} \varphi_g, & \text{if } (\|\theta_g\| < M_g) \\ \text{or } (\|\theta_g\| = M_g, -\theta_g^T \varphi_g \geq 0), \\ \varphi_g - \frac{\theta_g}{\|\theta_g\|^2} \theta_g^T \varphi_g, & \text{otherwise,} \end{cases} \quad (7)$$

where

$$\varphi_f = -\gamma_f E^T P \cdot B_c \frac{\partial \hat{f}}{\partial \theta_f}, \quad \gamma_f > 0,$$

$$\varphi_g = -\gamma_g E^T P \cdot B_c \frac{\partial \hat{g}}{\partial \theta_g} u_C, \quad \gamma_g > 0;$$

$$\frac{\partial \hat{f}}{\partial \theta_f} = \left[\frac{\partial \hat{f}}{\partial a_f}, \frac{\partial \hat{f}}{\partial b_f}, \frac{\partial \hat{f}}{\partial h_f}, \frac{\partial \hat{f}}{\partial K_{F0}}, \right.$$

$$\left. \frac{\partial \hat{f}}{\partial K_{F1}}, \dots, \frac{\partial \hat{f}}{\partial K_{FL}}, \frac{\partial \hat{f}}{\partial \mu_{10}}, \frac{\partial \hat{f}}{\partial \mu_{20}}, \dots \right]^T,$$

$$\frac{\partial \hat{f}}{\partial a_f} = \frac{\hat{f}}{a_f}, \quad \frac{\partial \hat{g}}{\partial h_g} = -b_g \hat{g} \cdot \left\{ 1 - \frac{\hat{g}}{2a_g} \right\},$$

$$\begin{aligned} \frac{\partial \hat{f}}{\partial b_f} &= \frac{a_f \{ h_f + \sum_{j=0}^J \sum_{i=1}^n [\mu_{ij} x_i(t - j \cdot \tau)] \}}{2} \left\{ 1 + \frac{\hat{f}}{a_f} \right\} \\ &\quad \times \left\{ 1 - \frac{\hat{f}}{a_f} \right\}, \end{aligned}$$

$$\frac{\partial \hat{f}}{\partial h_f} = \frac{a_f b_f}{2} \left\{ 1 + \frac{\hat{f}}{a_f} \right\} \left\{ 1 - \frac{\hat{f}}{a_f} \right\},$$

$$\frac{\partial \hat{f}}{\partial \mu_{ij}} = \frac{a_f b_f x_i(t - j \cdot \tau)}{2} \left\{ 1 + \frac{\hat{f}}{a_f} \right\} \left\{ 1 - \frac{\hat{f}}{a_f} \right\},$$

$$\frac{\partial \hat{f}}{\partial K_{Fl}} = \frac{a_f b_f d_{ff}(t - l \cdot \tau)}{2} \left\{ 1 + \frac{\hat{f}}{a_f} \right\} \left\{ 1 - \frac{\hat{f}}{a_f} \right\},$$

$$\frac{\partial \hat{g}}{\partial a_g} = \frac{\hat{g}}{a_g},$$

$$\begin{aligned}\frac{\partial \hat{g}}{\partial \theta_g} &= \left[\frac{\partial \hat{g}}{\partial a_g}, \frac{\partial \hat{g}}{\partial b_g}, \frac{\partial \hat{g}}{\partial h_g}, \frac{\partial \hat{g}}{\partial \mu_1}, \frac{\partial \hat{g}}{\partial \mu_2}, \dots \right]^T, \\ \frac{\partial \hat{g}}{\partial b_g} &= \left[-h_g + \sum_{i=1}^n \mu_i x_i(t) \right] \hat{g} \cdot \left\{ 1 - \frac{\hat{g}}{2a_g} \right\}, \\ \frac{\partial \hat{g}}{\partial \mu_i} &= b_g x_i(t) \hat{g} \cdot \left\{ 1 - \frac{\hat{g}}{2a_g} \right\}.\end{aligned}\quad (8)$$

The adaptation law, (4) and (5), is designed to ensure the boundedness of θ_f and θ_g . Substituting (2) into (1), we have

$$\begin{aligned}x^{(n)} &= f + g \cdot (u_C + u_S) + d_0 = y_r^{(n)} + K^T E \\ &+ [f - \hat{f}] + [g - \hat{g}] u_C + g \cdot u_S + d_0.\end{aligned}\quad (9)$$

This implies that

$$\dot{e}^{(n)} = -K^T E + \hat{f} - f + [\hat{g} - g] u_C - g \cdot u_S - d_0. \quad (10)$$

Let $A_c = \begin{bmatrix} 0_{(n-1) \times 1} & I_{(n-1) \times (n-1)} \\ -K^T & \end{bmatrix}$ and $B_c = [0_{1 \times (n-1)}, 1]^T$ be a companion form pair; we may rewrite (10) as

$$\dot{E} = A_c E + B_c \cdot \{\hat{f} - f + [\hat{g} - g] u_C - g \cdot u_S - d_0\}. \quad (11)$$

Now consider a Lyapunov function candidate

$$V_E = 2^{-1} E^T P \cdot E, \quad (12)$$

where $P > 0$ which satisfies the Lyapunov equation

$$A_c^T P + P \cdot A_c = -Q, \quad (13)$$

with Q being a positive definite symmetric matrix. In the subsequent derivation, we will choose Q such that

$\lambda_{\min}(Q) > 1$ with $\lambda_{\min}(Q)$ being the minimum eigenvalue of Q . Define

$$V_M = 2^{-1} \lambda_{\min}(P) (M_x - \|Y_r\|_{\infty})^2, \quad (14)$$

where M_x is a positive constant and $Y_r = [y_r, \dot{y}_r, \dots, y_r^{(n-1)}]^T$. Note that, if $\|x\| \geq M_x \geq \|Y_r(t)\|_{\infty} = \sup_{t \geq 0} \|Y_r(t)\|$, from (14), we have

$$\begin{aligned}V_E &\geq 2^{-1} \cdot \lambda_{\min}(P) \cdot \|E\|^2 \\ &\geq 2^{-1} \cdot \lambda_{\min}(P) \cdot (\|x\| - \|Y_r(t)\|)^2 \\ &\geq 2^{-1} \cdot \lambda_{\min}(P) \cdot (M_x - \|Y_r(t)\|_{\infty})^2 = V_M.\end{aligned}\quad (15)$$

Hence, if $V_E < V_M$, we have that $\|x\| < M_x$. Moreover, the derivative of V_E along the trajectories of the closed-loop system (11) satisfies

$$\begin{aligned}\dot{V}_E &= 2^{-1} E^T (A_c^T P + P A_c) E \\ &+ E^T P B_c \cdot [\hat{f} - f + (\hat{g} - g) u_C - g \cdot u_S - d_0] \\ &\leq -2^{-1} E^T Q E + |E^T P B_c| \\ &\quad \times [| \hat{f} | + |f| + | \hat{g} u_C | + |g u_C| + d_U] - E^T P B_c g u_S.\end{aligned}\quad (16)$$

From (16), if there exists a supervisory control law with

$$\begin{aligned}u_S &= I^* \operatorname{sgn} (E^T P B_c) g_L^{-1} (f_U + |g_U u_C| + |\hat{f}| + d_U + |\hat{g} u_C|),\end{aligned}\quad (17)$$

where f_U, g_L, g_U are boundary functions for f and g such that $0 \leq |f| \leq f_U$ and $0 < g_L \leq g \leq g_U$, then we can guarantee that

$$\dot{V}_E < 0, \quad \text{where } I^* = \begin{cases} 1, & \text{for } V_E \geq V_M, \\ 0, & \text{otherwise.} \end{cases} \quad (18)$$

For the following deviation, we define the modeling error

$$e_{\text{mod}} = \hat{f}(\theta_f^*) - f + [\hat{g}(\theta_g^*) - g] u_C - d_0, \quad (19)$$

where θ_f^* and θ_g^* are the optimal parameters. Then (11) can be rewritten using Taylor series expansions as

$$\begin{aligned}\dot{E} &= A_c E - B_c g u_S \\ &+ B_c \{ \hat{f}(\theta_f) - \hat{f}(\theta_f^*) + [\hat{g}(\theta_g) - \hat{g}(\theta_g^*)] u_C \\ &\quad + e_{\text{mod}} \}.\end{aligned}\quad (20)$$

We have

$$\begin{aligned}\hat{f}(\theta_f) - \hat{f}(\theta_f^*) &= (\theta_f - \theta_f^*)^T \frac{\partial \hat{f}(\theta_f)}{\partial \theta_f} + \varepsilon_f, \\ \hat{g}(\theta_g) - \hat{g}(\theta_g^*) &= (\theta_g - \theta_g^*)^T \frac{\partial \hat{g}(\theta_g)}{\partial \theta_g} + \varepsilon_g,\end{aligned}\quad (21)$$

with ε_f and ε_g being the approximation errors of higher order terms. Now consider another Lyapunov function candidate V_G given by

$$\begin{aligned}V_G &= 2^{-1} E^T P \cdot E + (2\gamma_f)^{-1} (\theta_f - \theta_f^*)^T (\theta_f - \theta_f^*) \\ &\quad + (2\gamma_g)^{-1} (\theta_g - \theta_g^*)^T (\theta_g - \theta_g^*).\end{aligned}\quad (22)$$

Using (20)–(22), we have

$$\begin{aligned}\dot{V}_G &= -2^{-1} E^T Q \cdot E + \gamma_f^{-1} \cdot (\theta_f - \theta_f^*)^T \\ &\quad \times \left[\dot{\theta}_f + \gamma_f E^T P \cdot B_c \frac{\partial \hat{f}(\theta_f)}{\partial \theta_f} \right] \\ &\quad + \gamma_g^{-1} \cdot (\theta_g - \theta_g^*)^T \left[\dot{\theta}_g + \gamma_g E^T P \cdot B_c \frac{\partial \hat{g}(\theta_g)}{\partial \theta_g} u_C \right] \\ &\quad - g \cdot E^T P \cdot B_c u_S + E^T P \cdot B_c \cdot [e_{\text{mod}} + \varepsilon_f + \varepsilon_g u_C].\end{aligned}\quad (23)$$

Furthermore, as $E(0)$, $e_{\text{mod}}(0)$, $u_C(0)$, d_0 , ε_f and ε_g are bounded, and the projection method of the adaptation laws

FIGURE 1: (a) Structure of the experimental setup. (b) A close view of the installation of heater, cooling pipe, and thermocouples in the water tank (with the cover being opened for observation). A 60 mm thick LDPE (low density polyethylene) foam insulates the tank and forms its cover.

FIGURE 2: Experimental records of temperature when the system was controlled by four different control schemes.

ensures the boundedness of u_C , there exists a boundary function $\tilde{e}$ such that

$$\begin{aligned} & \left| E^T P \cdot B_c \cdot [e_{\text{mod}} + \varepsilon_f + \varepsilon_g u_C] \right| \leq \tilde{e}, \\ & \dot{V}_G \leq -2^{-1} E^T Q E + \left| E^T P B_c [e_{\text{mod}} + \varepsilon_f + \varepsilon_g u_C] \right| \quad (24) \\ & \leq -2^{-1} \lambda_{\min}(Q) \|E\|^2 + \tilde{e}. \end{aligned}$$

This guarantees that $\dot{V}_G < 0$, if $\|E\| > (\sqrt{\tilde{e}} / \sqrt{2^{-1} \lambda_{\min}(Q)})$. From the two adaptation laws (6) and (7), we obtain that if (24) is satisfied, the system (1) is uniformly ultimately bounded (UUB) stable.

4. Experimental Study

Temperature control systems are among the nonlinear systems with significant delay effects.

The proposed control scheme has been implemented on a prototype temperature control system. The system includes a water tank, a water pump, a resistor heater which serves as disturbance, and four thermal couples, as shown in Figure 1. The 40 cm diameter tank is filled with water to a depth of 60 cm, the pump is driven by a 370 W frequency inverter, and

the heater is driven by a SSR power IC. The control objective is to maintain the water temperature around the desired value $y_r = 30^\circ\text{C}$.

The function and gains of the supervisory control law (17) are given as $f_U(X) = 1 + 0.004x_2^2$, $g_L = 2$, $g_U = 2.2$. Moreover, we choose $k_0 = 0.3$ and $k_1 = 0.01$ so that the roots of $s^2 + k_1s + k_0 = 0$ are in the left-half complex plane. For (11), we have $A_c = \begin{bmatrix} 0 & 1 \\ -0.3 & -0.01 \end{bmatrix}$ and $B_c = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$. Besides, with $Q = \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix}$ for (13), we have $P = \begin{bmatrix} 1.3003 \times 10^3 & 33.3333 \\ 33.3333 & 4.3333 \times 10^3 \end{bmatrix}$.

In designing the supervisory control law, we choose $M_X = 0.25$ for (14) and $M_f = 4$, $M_g = 4$, $\gamma_f = 1.6 \times 10^{-3}$, and $\gamma_g = 0.8 \times 10^{-6}$ for the adaptation laws (6) and (7).

For comparison, three different control schemes were implemented based on similar initial states around $x_1(0) = \xi(0) = 30^\circ\text{C}$ and $x_2(0) = \dot{\xi}(0) = 0$:

- (1) the PD controller, $u(t) = K_P e(t) + K_D \dot{e}(t)$, which was exhaustively tuned for best tracking performance to be with $K_P = 0.3$ and $K_D = 0.05$,
- (2) the proposed control scheme without the feed-forwarded disturbance term $w_m(t)$. That is, $K_{F0} = \dots = K_{FL} = 0$ in (5),
- (3) the proposed control scheme.

Experimental results, shown in Figure 2, demonstrate that, in the face of disturbances, the output fluctuation was within $30 \pm 0.42^\circ\text{C}$ for (1), within $30 \pm 0.25^\circ\text{C}$ for (2), and within $30 \pm 0.15^\circ\text{C}$ using the proposed control scheme. It is clear that the proposed scheme was able to achieve accurate tracking performance in the face of measurable or predictable disturbance. Furthermore, under the condition of immeasurable disturbance, temperature of the adaptively controlled system, the control scheme of (2), suffered from larger fluctuation but is still better than that of the PD controlled system, demonstrating effectiveness of the adaptation for the nonlinear and delayed temperature control system.

5. Conclusion

We proposed a simple yet effective adaptive neural control scheme for delayed nonlinear systems. Experimental results validate its effectiveness and show that the feed-forward of disturbance, if available, can achieve further improvements. It is clear that the proposed scheme has an excellent regulation performance when compared with PD control law, and the feedforward term can achieve further improvements.

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