Time-delay Positive Feedback Control for Nonlinear Time-delay Systems with Neural Network Compensation

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Abstract A new adaptive time-delay positive feedback controller (ATPFC) is presented for a class of nonlinear time-delay systems. The proposed control scheme consists of a neural networks-based identification and a time-delay positive feedback controller. Two high-order neural networks (HONN) incorporated with a special dynamic identification model are employed to identify the nonlinear system. Based on the identified model, local linearization compensation is used to deal with the unknown nonlinearity of the system. A time-delay-free inverse model of the linearized system and a desired reference model are utilized to constitute the feedback controller, which can lead the system output to track the trajectory of a reference model. Rigorous stability analysis for both the identification and the tracking error of the closed-loop control system is provided by means of Lyapunov stability criterion. Simulation results are included to demonstrate the effectiveness of the proposed scheme.

Key words Time-delay system, neural networks, system identification, adaptive control, linearization compensation

Time-delay is unavoidable in many control systems due to the transmission delay of control information between different parts of the system (e.g., telerobot control systems, networked control systems, or process control systems). The presence of time-delay may lead to a sluggish response, limit the achievable performance of controller, and even trigger instability of the closed-loop systems.

The research on on-line identification and control for linear time-delay systems has been around for several decades[1−4]. However, only a few time-delay compensation strategies and control structures are currently available for nonlinear time-delay systems, such as nonlinear Smith predictor[5], nonlinear internal model control with feedback compensation (IMC-FC)[6], and input-output linearization compensation algorithm[7]. Mainly, these methods focus on the regulation problem and are only valid for partially known processes. If the system model does not match the time-delay plant exactly (i.e., system dynamics are unknown or with remarkable disturbance), the control system would become unstable. In this paper, an adaptive time-delay positive feedback control (ATPFC) scheme is investigated for a class of unknown nonlinear affine time-delay systems. First, a special dynamic identification model including two high-order neural networks (HONN) is constructed to estimate the unknown nonlinear time-delay systems. Based on the identified model, local NN-based linearization compensation technology is then employed to deal with the unknown nonlinearity of the system. For the local linearized system, an adaptive time-delay positive feedback controller is directly designed to guarantee the tracking performance.

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The roots of our ATPFC can go back to the adaptive time-delay controller (ATDC)[8], which is only suitable for linear time-delay systems. However, the application of ATDC is limited because such a scheme cannot deal with the nonlinear time-delay system, and there are no theoretic results on the stability analysis of the control system. The main contribution of this paper is that NN-based local linearization compensation is investigated originally in order to extend the principle of ATDC to nonlinear time-delay systems and to improve the robust performance of the closed-loop control system. Furthermore, the stability analysis of ATDC strategy incorporating with HONNs identification and linearization compensation is also given based on Lyapunov theory. The notion of combining adaptive technology[9] with neural identification[10−12] is utilized to deduce the adaptive weights updating-law of HONNs, and thus, no off-line learning phase[13] is required. A salient characteristic of the resulting method is that it is a time-delay independent strategy, which can deprive the time-delay from the overall closed-loop system.

The remainder of paper is organized as follows. Background and problem statement are given in Section 1. In Section 2, the special dynamic identification model is employed to identify the unknown nonlinear time-delay system. Section 3 describes the implementation of adaptive time-delay positive feedback controller with HONNs-based linearization compensation. Section 4 evaluates the proposed algorithms with simulation. Conclusions are presented in Section 5.

1 Background and problem statement

Consider a class of single-input single-output (SISO) nonlinear affine systems with input time-delay described by state-space representation

$$\begin{aligned} &\dot{x}_1(t) = x_2(t) \\ &\cdots\cdots \\ &\dot{x}_n(t) = f(\bar{\boldsymbol{x}}(t)) + g(\bar{\boldsymbol{x}}(t))u(t-\tau) + d(t) \\ &y(t) = x_1(t) \end{aligned} \tag{1}$$

or equivalent differential equation as below

$$y^{(n)}(t) = f(\bar{\boldsymbol{x}}(t)) + g(\bar{\boldsymbol{x}}(t))u(t-\tau) + d(t) \tag{2}$$

where $\bar{\boldsymbol{x}}(t) = [x_1(t), x_2(t), \cdots, x_n(t)]^{\mathrm{T}} = [y(t), \dot{y}(t), \cdots, y^{(n-1)}(t)]^{\mathrm{T}} \in \mathbf{R}^n$, $u(t) \in \mathbf{R}$, and $y(t) \in \mathbf{R}$ are the state variables, input, and output of the system, respectively; $f(\bar{\boldsymbol{x}}), g(\bar{\boldsymbol{x}}) : \mathbf{R}^n \rightarrow \mathbf{R} \in \mathbf{C}(s)$ are unknown nonlinear smooth functions; τ is a known constant time delay; $d(t)$ is an unknown disturbance bounded by $|d(t)| \leq D$ with the positive constant D.

The control objective can be described as: given a desired trajectory $y_m(t)$, which is the output of a reference model (3), to find a control $u(t)$, such that the system output $y(t)$ tracks the delayed trajectory $y_m(t-\tau)$ with an acceptable accuracy, while all signals of the control system remain bounded.

$$y_m^{(n)}(t) = -\sum_{i=0}^{n-1} a_i y_m^{(i)}(t) + R(t) \tag{3}$$

where $A(s) = s^n + a_{n-1}s^{n-1} \cdots + a_0$ is a Hurwitz polynomial, which will be used as a part of our controller. $R(t)$ is a bounded input to the model (3) and the whole control system.

Assumption 1. The sign of $g(\bar{\boldsymbol{x}})$ is positive, and there exists a known constant $g_0 > 0$, such that $g(\bar{\boldsymbol{x}}) > g_0 > 0$, $\forall \bar{\boldsymbol{x}} \in \mathbf{R}^n$.

Remark 1. The desired reference model (3) can be rewritten as a transfer function

$$\frac{1}{A(s)} = \frac{1}{s^n + a_{n-1}s^{n-1} + \cdots + a_0}$$

$A(s)$ can be selected by designers to satisfy the required system response with the given input $R(t)$.

From now on, without special description, $\mathbf{R}, \mathbf{R}^n$, and $\mathbf{R}^{m\times n}$ denote the real number set, the real n-vector set, and the real $m \times n$ matrix set, respectively. The $\|\bullet\|$ denotes any suitable norm, where $\|A\boldsymbol{x}\|_2 \le \|A\|_F \|\boldsymbol{x}\|_2$ with $\boldsymbol{x} \in \mathbf{R}^n$, and $A \in \mathbf{R}^{m\times n}$. To avoid cluttering the notation, the argument of all time signals will be omitted except for the case when it appears delayed or it is necessary

2 Neural network identification for nonlinear time-delay system

The design of the adaptive control scheme for the time-delay nonlinear system (1) proceeds in two steps. First, we employ a special dynamic identification with two neural networks to identify the unknown nonlinear time-delay system in this section. Then, an adaptive time-delay positive feedback controller incorporating with linearization compensation is presented in Section 3.

As a typical kind of linearly parameterized neural network that is widely used in the identification and control of nonlinear systems[14−17], the high-order neural network can emulate a nonlinear function up to a small error tolerance over a compact set.

For system (2), the identification model can be described by the following differential equation with HONNs

$$\hat{y}_p^{(n)} = -\sum_{i=0}^{n-1} a_i \hat{y}_p^{(i)} + \hat{\boldsymbol{W}}_1^{\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \hat{\boldsymbol{W}}_2^{\rm T}\boldsymbol{\Phi}_2(\bar{\boldsymbol{x}})u(t-\tau) + \xi(t) \tag{4}$$

where $\xi(t)$ is a robust modification term provided by (12), which can guarantee the convergence of the identification error; $\bar{\boldsymbol{x}}(t) = [y(t), \dot{y}(t), \cdots, y^{(n-1)}(t)]^{\rm T} \in \mathbf{R}^n$ is the input to the neural networks and $\bar{\boldsymbol{x}}_p(t) = [\hat{y}_p(t), \dot{\hat{y}}_p(t), \cdots, \hat{y}_p^{(n-1)}(t)]^{\rm T} \in \mathbf{R}^n$ is the output of identification; $\hat{\boldsymbol{W}}_i = [\hat{w}_{i1}, \hat{w}_{i2}, \cdots, \hat{w}_{iL_i}]^{\rm T} \in \mathbf{R}^{L_i} (i = 1, 2)$ are the estimated weight vectors; $L_i (i = 1, 2)$ are the numbers of the neurons, and $\boldsymbol{\Phi}_i(\bar{\boldsymbol{x}}) \in \mathbf{R}^{L_i} (i = 1, 2)$ are L_i-vectors with the element $\Phi_{ik}(\bar{\boldsymbol{x}}), k = 1, \cdots, L_i (i = 1, 2)$ of the form

$$\Phi_{ik}(x) = \prod_{j\in J_{ik}} [\sigma(y^{(j)})]^{d_k(i)} \tag{5}$$

where $J_{ik} (k = 1, \cdots, L_i; i = 1, 2)$ are collections of L_i unordered subsets of $\{0, 1, \cdots, n-1\}$; $d_k(i) (k = 1, \cdots, L_i; i = 1, 2)$ are nonnegative integers.

The function $\sigma(\cdot)$ is a monotonically increasing, differentiable function, which is usually represented by sigmoid form

$$\sigma(x) = \frac{a}{1 + {\rm e}^{-bx}} - c \tag{6}$$

where parameters a and b are positive real numbers that represent the bound and slope of the sigmoidal curvature, and c is a real number that denotes a bias constant, respectively.

Due to the approximation error of the neural networks, there exist ideal weights $\boldsymbol{W}_i^* = [w_{i1}^*, w_{i2}^*, \cdots, w_{iL_i}^*]^{\rm T} \in \mathbf{R}^{L_i} (i = 1, 2)$ and reconstruction errors $\varepsilon_i (i = 1, 2)$, such that system (2) can be described as

$$\begin{aligned} y^{(n)} = & -\sum_{i=0}^{n-1} a_i y^{(i)} + \boldsymbol{W}_1^{*\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 + \\ & [\boldsymbol{W}_2^{*\rm T}\boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) + \varepsilon_2]u(t-\tau) + d \end{aligned} \tag{7}$$

The following standard assumptions are stated:

Assumption 2. The approximation errors ε_i are bounded by $|\varepsilon_i| \le \varepsilon_{iN}, i = 1, 2$, with $\varepsilon_{iN} \ge 0$.

Assumption 3. The optimal weight vectors $\boldsymbol{W}_i^*$ are bounded by $||\boldsymbol{W}_i^*|| \le W_{iN}, i = 1, 2$, with $W_{iN} \ge 0$.

Remark 2. The term $-\sum_{i=0}^{n-1} a_i y^{(i)}$ is added into system (7), and the function $f(\bar{\boldsymbol{x}}) + \sum_{i=0}^{n-1} a_i y^{(i)}$ is estimated by a HONN:

$$\begin{aligned} \sum_{i=0}^{n-1} a_i y^{(i)} + f(\bar{\boldsymbol{x}}) = & \boldsymbol{W}_1^{*\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 = \\ & \hat{\boldsymbol{W}}_1^{\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \tilde{\boldsymbol{W}}_1^{\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 \end{aligned} \tag{8}$$

where $\tilde{\boldsymbol{W}}_i = \boldsymbol{W}_i^* - \hat{\boldsymbol{W}}_i, i = 1, 2$, are the estimated weight error vectors.

Then, in the next section, $\hat{\boldsymbol{W}}_1^{\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}})$, $\hat{\boldsymbol{W}}_2^{\rm T}\boldsymbol{\Phi}_2(\bar{\boldsymbol{x}})$ will be used as linearization compensation terms, which can cancel the unknown nonlinear dynamic $f(\bar{\boldsymbol{x}})$ and $g(\bar{\boldsymbol{x}})$ of system (2). Thus, system (2) will become a local linear time-delay plant.

Define the identification error vector as

$$\bar{\boldsymbol{e}}(t) = \bar{\boldsymbol{x}}(t) - \bar{\boldsymbol{x}}_p(t) = [y - \hat{y}_p, \dot{y} - \dot{\hat{y}}_p, \cdots, y^{(n-1)} - \hat{y}_p^{(n-1)}]^{\rm T} \tag{9}$$

and the filtered identification error as

$$r(t) = [\ \bar{\boldsymbol{\lambda}}^{\rm T} \quad 1\ ]\bar{\boldsymbol{e}}(t) \tag{10}$$

where $\bar{\boldsymbol{\lambda}} = [\lambda_1, \lambda_2, \cdots, \lambda_{n-1}]^{\rm T}$ is an appropriately chosen vector (i.e., $s^{n-1} + \lambda_{n-1}s^{n-2} + \cdots + \lambda_1$ is Hurwitz), so that $\bar{\boldsymbol{e}}(t) \to 0$ as $r(t) \to 0$. Subtracting (4) into (7), we obtain the error equation

$$\begin{aligned} y^{(n)} - \hat{y}_p^{(n)} = & -\sum_{i=0}^{n-1} a_i (y^{(i)} - \hat{y}_p^{(i)}) + \tilde{\boldsymbol{W}}_1^{\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 + \\ & (\tilde{\boldsymbol{W}}_2^{\rm T}\boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) + \varepsilon_2)u(t-\tau) - \xi(t) + d \end{aligned} \tag{11}$$

A choice of the robust modification term $\xi(t)$ is

$$\begin{aligned} \xi(t) = & k_v r(t) + [\ 0 \quad \bar{\boldsymbol{\lambda}}^{\rm T}\ ]\bar{\boldsymbol{e}}(t) - [a_0, \cdots, a_{n-1}]\bar{\boldsymbol{e}}(t) = \\ & k_v r(t) + [-a_0, \lambda_1 - a_1, \cdots, \lambda_{n-1} - a_{n-1}]\bar{\boldsymbol{e}}(t) \end{aligned} \tag{12}$$

where k_v is a positive parameter. Then, from (9) ∼ (11), the time derivative of the filtered error can be written as

$$\begin{aligned} \dot{r}(t) = & -k_v r(t) + \tilde{\boldsymbol{W}}_1^{\rm T}\boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 + \\ & \tilde{\boldsymbol{W}}_2^{\rm T}\boldsymbol{\Phi}_2(\bar{\boldsymbol{x}})u(t-\tau) + \varepsilon_2 u(t-\tau) + d \end{aligned} \tag{13}$$

Remark 3. In this section, the control input $u(t)$ of system (2) is assumed to be bounded for all $t > 0$. This assumption is required for system identification. The convergence of identification (4) is ensured only if the input $u(t)$ is bounded.

Generally, the nonlinear separation principle is not valid, thus this assumption is quite restrictive for a control system. However, it will be guaranteed when the identification is combined with a time-delay positive feedback controller in the closed-loop system in Section 3. We will provide the stability proof of the overall system there, including identification and controller simultaneously, and the assumption will be eliminated then. But now, we consider $u(t) < U$ with $U \geq 0$, in order to show the completeness of the identification design.

Define $\Omega_2 = \{\hat{\boldsymbol{W}}_2 \in \mathbf{R}^{L_2} | \mathbf{g}(\hat{\boldsymbol{W}}_2) = g_0 - \hat{\boldsymbol{W}}_2 \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) \leq 0\}$ as the compact set of $\hat{\boldsymbol{W}}_2$. In order to ensure that the Assumption 1 is satisfied, the adaptive weight updating laws of HONNs are provided by

$$\left\{ \begin{array}{l} \dot{\hat{\boldsymbol{W}}}_1 = F_1 \boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) r - K_e F_1 |r| \hat{\boldsymbol{W}}_1 \\ \dot{\hat{\boldsymbol{W}}}_2 = \mathrm{Proj}(F_2 \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) r u(t-\tau) - K_e F_2 |r| \hat{\boldsymbol{W}}_2) \end{array} \right. \tag{14}$$

with the design parameters $F_i > 0, K_e > 0, i = 1, 2$. The projection algorithm $\mathrm{Proj}(\cdot)$ is defined as in [9]

$$\mathrm{Proj}(\boldsymbol{\theta}) = \left\{ \begin{array}{ll} \boldsymbol{\theta}, & \text{if } \hat{\boldsymbol{W}}_2 \in \Omega_2 \text{ or } \hat{\boldsymbol{W}}_2 \in \delta\Omega_2 \text{ and } \boldsymbol{\theta}^{\mathrm{T}} \nabla \mathbf{g} \leq 0 \\ \boldsymbol{\theta} - \dfrac{(\nabla \mathbf{g} \nabla \mathbf{g}^{\mathrm{T}})}{\nabla \mathbf{g}^{\mathrm{T}} \nabla \mathbf{g}} \boldsymbol{\theta}, & \text{otherwise} \end{array} \right.$$

where $\boldsymbol{\theta} = F_2 \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) r u(t-\tau) - K_e F_2 |r| \hat{\boldsymbol{W}}_2$.

Theorem 1. Given Assumptions 1 ∼ 3 and Remark 3, consider system (2) with the identification model described in (4), and the HONN weight updating laws (14). Then, the filtered identification error $r(t)$ and estimated weight errors $\tilde{\boldsymbol{W}}_i, i = 1, 2$ are uniformly ultimately bounded (UUB).

Proof. Select the Lyapunov function

$$V = \frac{1}{2} r^2 + \frac{1}{2} \tilde{\boldsymbol{W}}_1^{\mathrm{T}} F_1^{-1} \tilde{\boldsymbol{W}}_1 + \frac{1}{2} \tilde{\boldsymbol{W}}_2^{\mathrm{T}} F_2^{-1} \tilde{\boldsymbol{W}}_2 \tag{15}$$

Differentiating V along the trajectory (13) and (14) yields

$$\begin{aligned} \dot{V} = & r\dot{r} + \tilde{\boldsymbol{W}}_1^{\mathrm{T}} F_1^{-1} \dot{\tilde{\boldsymbol{W}}}_1 + \tilde{\boldsymbol{W}}_2^{\mathrm{T}} F_2^{-1} \dot{\tilde{\boldsymbol{W}}}_2 = \\ & -k_v r^2 + \tilde{\boldsymbol{W}}_1^{\mathrm{T}} \boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) r + \tilde{\boldsymbol{W}}_2^{\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) r u + \varepsilon_1 r + \varepsilon_2 u r + \\ & r d + \tilde{\boldsymbol{W}}_1^{\mathrm{T}} F_1^{-1} (-F_1 \boldsymbol{\Phi}_1^{\mathrm{T}}(\bar{\boldsymbol{x}}) r + K_e F_1 |r| \hat{\boldsymbol{W}}_1) + \\ & \tilde{\boldsymbol{W}}_2^{\mathrm{T}} F_2^{-1} (-F_2 \boldsymbol{\Phi}_2^{\mathrm{T}}(\bar{\boldsymbol{x}}) r u + K_e F_2 |r| \hat{\boldsymbol{W}}_2) = \\ & -k_v r^2 + K_e |r| \tilde{\boldsymbol{W}}_1^{\mathrm{T}} \hat{\boldsymbol{W}}_1 + K_e |r| \tilde{\boldsymbol{W}}_2^{\mathrm{T}} \hat{\boldsymbol{W}}_2 + r \Delta\delta \end{aligned} \tag{16}$$

where $\Delta\delta = \varepsilon_1 + \varepsilon_2 u + d < \varepsilon_{1N} + \varepsilon_{2N} U + D$ is a bounded error.

Since $\tilde{\boldsymbol{W}}_i^{\mathrm{T}} \hat{\boldsymbol{W}}_i = \tilde{\boldsymbol{W}}_i^{\mathrm{T}} (\boldsymbol{W}_i^* - \tilde{\boldsymbol{W}}_i) = \langle \tilde{\boldsymbol{W}}_i, \boldsymbol{W}_i^* \rangle - \|\tilde{\boldsymbol{W}}_i\|_F^2, i = 1, 2$, where $\langle \tilde{\boldsymbol{W}}, \boldsymbol{W}^* \rangle = \mathrm{tr}(\tilde{\boldsymbol{W}}^{\mathrm{T}} \boldsymbol{W}^*)$ and $\|\tilde{\boldsymbol{W}}\|_F^2 = \mathrm{tr}(\tilde{\boldsymbol{W}}^{\mathrm{T}} \tilde{\boldsymbol{W}})$ denote the inner product and the Frobenius norm, respectively, then

$$\begin{aligned} & \dot{V} \leq -k_v |r|^2 + K_e |r| \left(W_{1N} \left\| \tilde{\boldsymbol{W}}_1 \right\|_F - \left\| \tilde{\boldsymbol{W}}_1 \right\|_F^2 \right) + \\ & K_e |r| \left(W_{2N} \left\| \tilde{\boldsymbol{W}}_2 \right\|_F - \left\| \tilde{\boldsymbol{W}}_2 \right\|_F^2 \right) + |r| \Delta\delta \leq \\ & -|r| \left\{ k_v |r| + K_e \left(\left\| \tilde{\boldsymbol{W}}_1 \right\|_F - \frac{1}{2} W_{1N} \right)^2 + \right. \\ & \left. K_e \left(\left\| \tilde{\boldsymbol{W}}_2 \right\|_F - \frac{1}{2} W_{2N} \right)^2 - \left(\frac{K_e}{4} W_{1N}^2 + \frac{K_e}{4} W_{2N}^2 + \Delta\delta \right) \right\} \end{aligned} \tag{17}$$

From (17), it can be shown that $\dot{V}$ is negative if

$$|r| \geq \frac{K_e (W_{1N}^2 + W_{2N}^2) + 4\Delta\delta}{4 k_v} \tag{18}$$

$$\left\| \tilde{\boldsymbol{W}}_1 \right\|_F \geq \frac{1}{2} W_{1N} + \sqrt{\frac{K_e (W_{1N}^2 + W_{2N}^2) + 4\Delta\delta}{4 K_e}} \tag{19}$$

$$\left\| \tilde{\boldsymbol{W}}_2 \right\|_F \geq \frac{1}{2} W_{2N} + \sqrt{\frac{K_e (W_{1N}^2 + W_{2N}^2) + 4\Delta\delta}{4 K_e}} \tag{20}$$

Therefore, inequalities (18) ∼ (20) give the attractive compact sets for $\|\tilde{\boldsymbol{W}}_i\|_F$ and $|r|$, which means $\|\tilde{\boldsymbol{W}}_i\|_F$ and $|r|$ are uniformly ultimately bounded (UUB) based on the extended Lyapunov theorem. Then, from (10), the identification error vector $\bar{\boldsymbol{e}}(t)$ is also bounded. Furthermore, the boundedness of the filtered identification error $r(t)$ can be kept arbitrarily small if the gain k_v in the robust term is large enough. □

3 Adaptive time-delay positive feedback control

In this section, we investigate a NN-based local feedback linearization compensation technology to cancel unknown nonlinear terms of system (2), and then present an adaptive time-delay positive feedback control configuration to deal with the nonlinear affine time-delay system (2). The overall adaptive time-delay positive feedback control system is depicted in Fig. 1 (see next page).

Subtracting the compensation term $\hat{\boldsymbol{W}}_1^{\mathrm{T}} \boldsymbol{\Phi}_1(\bar{\boldsymbol{x}})$ from (2) and using (8), we get

$$\begin{aligned} y^{(n)} = & -\sum_{i=0}^{n-1} a_i y^{(i)} + \tilde{\boldsymbol{W}}_1^{\mathrm{T}} \boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 + \\ & (\boldsymbol{W}_2^{*\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) + \varepsilon_2) u(t-\tau) + d \end{aligned} \tag{21}$$

The projection algorithm given by (14) guarantees $\hat{\boldsymbol{W}}_2^{\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) \neq 0$, then from Fig. 1, we can obtain

$$u(t-\tau) = \frac{1}{\hat{\boldsymbol{W}}_2^{\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}})} u_1(t-\tau) \tag{22}$$

where $u_1(t)$ is the control signal from time-delay controller. Substituting (22) into (21) yields

$$\begin{aligned} y^{(n)} = & -\sum_{i=0}^{n-1} a_i y^{(i)} + \tilde{\boldsymbol{W}}_1^{\mathrm{T}} \boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 + \\ & \frac{\boldsymbol{W}_2^{*\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) + \varepsilon_2}{\hat{\boldsymbol{W}}_2^{\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}})} u_1(t-\tau) + d = \\ & -\sum_{i=0}^{n-1} a_i y^{(i)} + u_1(t-\tau) + \Delta L \end{aligned} \tag{23}$$

where $\Delta L = \tilde{\boldsymbol{W}}_1^{\mathrm{T}} \boldsymbol{\Phi}_1(\bar{\boldsymbol{x}}) + \varepsilon_1 + \dfrac{\tilde{\boldsymbol{W}}_2^{\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}}) + \varepsilon_2}{\hat{\boldsymbol{W}}_2^{\mathrm{T}} \boldsymbol{\Phi}_2(\bar{\boldsymbol{x}})} u_1(t-\tau) + d$ is modeling error.

According to the above local linearization compensation process, it is easy to note that system (2) is translated into a known local linear time-delay plant (23) with an external disturbance ΔL. The inverse of time-delay deprived part of the plant (23) can be obtained by filter technology. Then, we utilize the desired reference model (3) with a positive time-delay feedback term $\mathrm{e}^{-s\tau}$ to constitute the time-delay positive feedback controller.

From Fig. 1, define the control error $E(t)$ as

$$E(t) = R(t) - [y(t) - y_d(t-\tau)] = R(t) - e_c(t) \tag{24}$$

where $R(t)$ is the given bounded input of the whole system

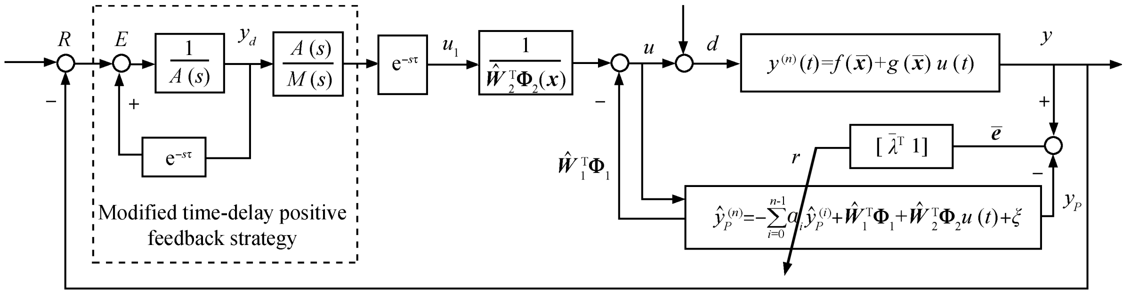


Fig. 1 Overall adaptive time-delay positive feedback control structure

and the reference model (3), $y(t)$ is the output of system (2), and $y_d(t-\tau)$ is the control feedback signal in the presented strategy, given by

$$y_d^{(n)}(t) = -\sum_{i=0}^{n-1} a_i y_d^{(i)}(t) + E(t) \tag{25}$$

Selecting a Hurwitz filter polynomial $M(s) = s^m + \sum_{i=0}^{m-1} m_i s^i$, where $m\,(m \geq n)$ is the order of the filter polynomial, we can obtain that the filter inverse of time-delay deprived part of system (23) is $A(s)/M(s)$. Therefore, the control signal of (23) is

$$u_1(s) = \frac{A(s)}{M(s)} y_d(s) = \frac{s^n + a_{n-1}s^{n-1} + \cdots + a_0}{s^m + m_{m-1}s^{m-1} + \cdots + m_0} y_d(s) \tag{26}$$

Denote the feedback error vector as

$$\begin{aligned}\bar{\boldsymbol{e}}_c(t) = \bar{\boldsymbol{y}}(t) - \bar{\boldsymbol{y}}_d(t-\tau) = [y(t) - y_d(t-\tau), \dot{y}(t) - \\ \dot{y}_d(t-\tau), \cdots, y^{(n-1)}(t) - y_d^{(n-1)}(t-\tau)]^{\mathrm{T}}\end{aligned} \tag{27}$$

where $\bar{\boldsymbol{y}}_d(t-\tau) = [y_d(t-\tau), \dot{y}_d(t-\tau), \cdots, y_d^{(n-1)}(t-\tau)]^{\mathrm{T}}$ and $\bar{\boldsymbol{y}}(t) = [y(t), \dot{y}(t), \cdots, y^{(n-1)}(t)]^{\mathrm{T}}$ are control feedback vector and output vector, respectively.

Considering (23), (25), and (27), we rewrite them into state space forms described by

$$\dot{\bar{\boldsymbol{y}}}(t) = A\bar{\boldsymbol{y}}(t) + \boldsymbol{D}_y \tag{28}$$

$$\dot{\bar{\boldsymbol{y}}}_d(t-\tau) = A\bar{\boldsymbol{y}}_d(t-\tau) + \boldsymbol{D}_d \tag{29}$$

$$\dot{\bar{\boldsymbol{e}}}_c = A\bar{\boldsymbol{e}}_c + \boldsymbol{D}_c \tag{30}$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -a_0 & -a_1 & -a_2 & \cdots & -a_{n-1} \end{bmatrix}$$

$$\boldsymbol{D}_y = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ u_1(t-\tau) + \Delta L \end{bmatrix}, \quad \boldsymbol{D}_d = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ E(t-\tau) \end{bmatrix}$$

$$\boldsymbol{D}_c = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ u_1(t-\tau) + \Delta L - E(t-\tau) \end{bmatrix} \tag{31}$$

Considering the definitions of feedback control error vector and (25), there exist constants $C_1, C_2 \geq 0$, such that

$$|E(t)| \leq C_1 \|\bar{\boldsymbol{y}}_d(t)\| + C_2 \tag{32}$$

Recalling the modeling error $\Delta\delta$ in (16) and ΔL in (23), and using that $M(s)$ and $A(s)$ are all stable polynomials, then from (26) ~ (32), it is easy to prove that

$$\|\boldsymbol{D}_c\| \leq k_1 \|\bar{\boldsymbol{y}}_d(t-\tau)\| + k_2 \tag{33}$$

$$|\Delta\delta| \leq k_3 \|\bar{\boldsymbol{y}}_d(t-\tau)\| + k_4 \tag{34}$$

where k_1, k_2, k_3, and $k_4 \geq 0$ are positive constants.

Theorem 2. Consider system (2) with HONN identification model (4) and NN-based linearization compensation (21) and (22), whose weight updating laws are given by (14), and the control law is chosen as (26). Then, for a properly chosen design parameter k_v, the following properties hold:

1) For any bounded input $R(t)$, the filtered identification error $r(t)$, the control feedback vector $\bar{\boldsymbol{y}}_d(t-\tau)$, and feedback error vector $\bar{\boldsymbol{e}}_c(t)$ are UUB;

2) All the signals in the closed-loop system are bounded;

3) The tracking error between system (2) and desired reference model (3) $e_t(t) = y(t) - y_m(t-\tau)$ is bounded.

Proof. Since A is a stable matrix, for any symmetric positive definite matrices Q_d, Q_c , there exist symmetric positive definite matrices P_d, P_c satisfying the following equations

$$\begin{aligned} A^{\mathrm{T}}P_d + P_dA = -Q_d \\ A^{\mathrm{T}}P_c + P_cA = -Q_c \end{aligned} \tag{35}$$

1) Select the Lyapunov function candidate

$$\begin{aligned} V(t) =& \frac{1}{2}\{\tilde{\boldsymbol{W}}_1^{\mathrm{T}}(t)F_1^{-1}\tilde{\boldsymbol{W}}_1(t) + \tilde{\boldsymbol{W}}_2^{\mathrm{T}}(t)F_2^{-1}\tilde{\boldsymbol{W}}_2(t) + \\ & r^2(t) + \bar{\boldsymbol{e}}_c^{\mathrm{T}}(t)P_c\bar{\boldsymbol{e}}_c(t) + \bar{\boldsymbol{y}}_d^{\mathrm{T}}(t-\tau)P_d\bar{\boldsymbol{y}}_d^{\mathrm{T}}(t-\tau)\} \end{aligned} \tag{36}$$

Taking the time derivative of (36) along (13) ~ (14), (29) ~ (30), and using (32) ~ (34), we can get[1]

$$\begin{aligned} \dot{V} =\ & r\dot{r} + \tilde{\boldsymbol{W}}_1^{\mathrm{T}}F_1^{-1}\dot{\tilde{\boldsymbol{W}}}_1 + \tilde{\boldsymbol{W}}_2^{\mathrm{T}}F_2^{-1}\dot{\tilde{\boldsymbol{W}}}_2 + \frac{1}{2}\dot{\bar{\boldsymbol{e}}}_c^{\mathrm{T}}P_c\bar{\boldsymbol{e}}_c + \\ & \frac{1}{2}\bar{\boldsymbol{e}}_c^{\mathrm{T}}P_c\dot{\bar{\boldsymbol{e}}}_c + \frac{1}{2}\dot{\bar{\boldsymbol{y}}}_d^{\mathrm{T}}P_d\bar{\boldsymbol{y}}_d + \frac{1}{2}\bar{\boldsymbol{y}}_d^{\mathrm{T}}P_d\dot{\bar{\boldsymbol{y}}}_d = \\ & -k_vr^2 + K_e|r|\tilde{\boldsymbol{W}}_1^{\mathrm{T}}\hat{\boldsymbol{W}}_1 + k_e|r|\tilde{\boldsymbol{W}}_2^{\mathrm{T}}\hat{\boldsymbol{W}}_2 + r\Delta\delta - \\ & \frac{1}{2}\bar{\boldsymbol{e}}_c^{\mathrm{T}}Q_c\bar{\boldsymbol{e}}_c + \bar{\boldsymbol{e}}_c^{\mathrm{T}}P_c\boldsymbol{D}_c - \frac{1}{2}\bar{\boldsymbol{y}}_d^{\mathrm{T}}Q_d\bar{\boldsymbol{y}}_d + \bar{\boldsymbol{y}}_d^{\mathrm{T}}P_d\boldsymbol{D}_d \end{aligned} \tag{37}$$

[1] For convenience of notation, the argument of time-delay in $\bar{\boldsymbol{y}}_d(t-\tau)$ is also omitted during the proof of the Theorem 2.

Similar to (17), we can prove that

$$\tilde{\boldsymbol{W}}_i^{\mathrm{T}}\hat{\boldsymbol{W}}_i \leq -\left(\left\|\tilde{\boldsymbol{W}}_i\right\|_F - \frac{1}{2}W_{iN}\right)^2 + \frac{1}{4}W_{iN}^2 \tag{38}$$

Applying $ab \leq (a^2+k^2b^2)/2k,\ \ k=1$, we can get the following result from (37)

$$\begin{aligned}\dot{V}(t) \leq & -k_v\,|r|^2 + \frac{K_e}{4}\,|r|\,(W_{1N}^2+W_{2N}^2) + |r|\,k_3\,\|\bar{\boldsymbol{y}}_d\| + \\ & |r|\,k_4 - \frac{1}{2}\lambda_m(Q_c)\,\|\bar{\boldsymbol{e}}_c\|^2 + \lambda_M(P_c)\,\|\bar{\boldsymbol{e}}_c\|\,k_1\,\|\bar{\boldsymbol{y}}_d\| + \\ & \lambda_M(P_c)\,\|\bar{\boldsymbol{e}}_c\|\,k_2 - \frac{1}{2}\lambda_m(Q_d)\,\|\bar{\boldsymbol{y}}_d\|^2 + \\ & \lambda_M(P_d)\,\|\bar{\boldsymbol{y}}_d\|\,(C_1\,\|\bar{\boldsymbol{y}}_d\| + C_2) \leq \\ & |r|\,\{-(k_v - \frac{k_3}{2})\,|r| + \frac{K_e}{4}(W_{1N}^2+W_{2N}^2) + k_4\} + \\ & \|\bar{\boldsymbol{e}}_c\|\,\{-(\frac{1}{2}\lambda_m(Q_c) - \frac{k_1}{2}\lambda_M(P_c))\,\|\bar{\boldsymbol{e}}_c\| + \\ & \lambda_M(P_c)k_2\} + \|\bar{\boldsymbol{y}}_d\|\,\{-(\frac{1}{2}\lambda_m(Q_d) - \lambda_M(P_d)C_1 - \\ & \frac{k_3}{2} - \frac{k_1}{2}\lambda_M(P_c))\,\|\bar{\boldsymbol{y}}_d\| + \lambda_M(P_d)C_2\}\end{aligned} \tag{39}$$

where $\lambda_m(\cdot)$ and $\lambda_M(\cdot)$ denote the minimum and maximum eigenvalues of the corresponding matrix, respestinely.

From inequity (39), $\dot{V}(t)$ is negative if the following conditions hold

$$|r(t)| \geq \frac{K_e(W_{1N}^2+W_{2N}^2)+4k_4}{4k_v-2k_3} \tag{40}$$

$$\|\bar{\boldsymbol{e}}_c(t)\| \geq \frac{2\lambda_M(P_c)k_2}{\lambda_m(Q_c)-\lambda_M(P_c)k_1} \tag{41}$$

$$\|\bar{\boldsymbol{y}}_d(t-\tau)\| \geq \frac{2\lambda_M(P_d)C_2}{\lambda_m(Q_d)-2\lambda_M(P_d)C_1-k_3-k_1\lambda_M(P_c)} \tag{42}$$

Since the Lyapunov function $V(t)$ is nonnegative, we conclude from (40) ∼ (42) that the filtered identification error $r(t)$, the control feedback vector $\bar{\boldsymbol{y}}_d(t-\tau)$, and the feedback error vector $\bar{\boldsymbol{e}}_c(t)$ are UUB simultaneously.

2) The given reference input $R(t)$, the control feedback vector $\bar{\boldsymbol{y}}_d(t-\tau)$, and the feedback error $\bar{\boldsymbol{e}}_c(t)$ are bounded, then according to (24) and (27), we can draw the conclusion that the system output $y(t)$ and the control error $E(t)$ are all bounded, and then $y_d(t)$ is also bounded based on (25). Furthermore, since $M(s)$ and $A(s)$ are all stable polynomials, the control signal $u_1(t)$ is bounded from (26). This indicates that the boundedness of $u_1(t)$ can be guaranteed when we close the feedback loop.

3) According to (24) ∼ (34) and the fact that feedback error $\bar{e}_c(t)$ is bounded, the reference model (3) and system (23) can be rewritten as

$$\begin{aligned}y_m^{(n)}(t-\tau) = & -\sum_{i=0}^{n-1} a_i y_m^{(i)}(t-\tau) + R(t-\tau) = \\ & -\sum_{i=0}^{n-1} a_i y_m^{(i)}(t-\tau) + E(t-\tau) + \varepsilon_m\end{aligned} \tag{43}$$

$$\begin{aligned}y^{(n)}(t) = & -\sum_{i=0}^{n-1} a_i y^{(i)}(t) + u_1(t-\tau) + \Delta L = \\ & -\sum_{i=0}^{n-1} a_i y^{(i)}(t) + E(t-\tau) + \varepsilon_y\end{aligned} \tag{44}$$

where ε_m and ε_y also denote bounded errors.

Considering the tracking error $e_t(t) = y(t) - y_m(t-\tau)$, then

$$e_t^{(n)}(t) + \sum_{i=0}^{n-1} a_i e_t^{(i)}(t-\tau) = D_t \tag{45}$$

where $D_t = \varepsilon_y - \varepsilon_m$ is also bounded. Since $A(s)$ is a stable polynomial, $e_t(t)$ will converge to a small residual set around the origin. The filter $M(s)$ is selected carefully by designers to make the inverse of time-delay deprived plant $A(s)/M(s)$ proper in (26) and to reduce the tracking error $e_t(t)$ in (45). □

Remark 4. For the stability proof of the identification (4), we assume that the control signal $u(t)$ is bounded for all $t > 0$ in Remark 3. However, in Theorem 2 that guarantees the stability of the whole closed-loop system, we proved that the identification error and control error are all bounded simultaneously without this assumption. The filtered identification error $r(t)$ is combined with the control feedback $\bar{\boldsymbol{y}}_d(t-\tau)$ and feedback error $\bar{\boldsymbol{e}}_c(t)$ in Lyapunov function (36), such that the requirement of the boundedness on the control signal $u(t)$ is replaced by the boundedness on $y_d(t)$ from (26), which is reasonable base on Theorem 2. This means that the assumption of the control $u(t)$ in Section 2 can be eliminated.

Remark 5. Since the local linearized system (23) can be divided into a rational linear part and a pure time delay after local linearization compensation, the proposed control strategy for the nonlinear time-delay system is a time-delay independent method. When we choose any time delay, e.g. $\tau = 1\,\mathrm{s}$ or $4\,\mathrm{s}$, the proposed scheme is valid too.

4 Simulation

In this section, two simulation examples are included to illustrate the effectiveness of the proposed adaptive time-delay positive feedback controller with neural identification and compensation.

Example 1. Consider the Vander Poloscillator system with input-time delay

$$\ddot{y}(t) = (1-y^2(t))\dot{y}(t) - y(t) + (1+y^2(t)+\dot{y}^2(t))u(t-\tau) \tag{46}$$

The desired reference model is selected as

$$\ddot{y}_m(t) = -4\dot{y}_m(t) - 4y_m(t) + 4R(t) \tag{47}$$

This means $A(s) = s^2+4s+4$. We choose the filter polynomial $M(s) = 0.64\,s^2+1.6s+1$. The time delay is $\tau = 1\,\mathrm{s}$ and the sampling interval is 0.01 s. The reference input of the system is $R(t) = \sin(\pi t/3)$. The parameters of HONNs are $L_1 = L_2 = 8$, and $a = 2, b = 0.5$, and $c = 0.5$ are the parameters of the sigmoid function. The initial simulation conditions and other control parameters are given by

$$\begin{aligned}& y(0) = \dot{y}(0) = 0.1, \quad y_m(0) = \dot{y}_m(0) = 0 \\ & y_d(0) = \dot{y}_d(0) = 0, \quad \hat{\boldsymbol{W}}_1(0) = \hat{\boldsymbol{W}}_2(0) = [0,\cdots,0]^{\mathrm{T}} \\ & F_1 = F_2 = 100, \quad K_e = 1, \quad k_v = 100, \quad \lambda_1 = 10\end{aligned} \tag{48}$$

The proposed identification and adaptive time-delay positive feedback control are utilized. Fig. 2 shows the corresponding performance. The actual output $y(t)$ and the delayed desired trajectory $y_m(t-\tau)$ are shown in Fig. 2 (a). The history of the bounded control input $u_1(t)$ is indicated in Fig. 2 (b). The boundedness of the identification error $e\,(t) = y\,(t) - y_p\,(t)$ is given in Fig. 2 (c), and the Fig. 2 (d) depicts the HONNs estimated weights norm. The simulation results depicted in Fig. 2 show that the satisfying tracking performance is obtained.

Example 2. To evaluate the robust performance of the ATPFC, the simulation is done again for a practical cement mill system (CMS), which is a linear system with large time-delay given by

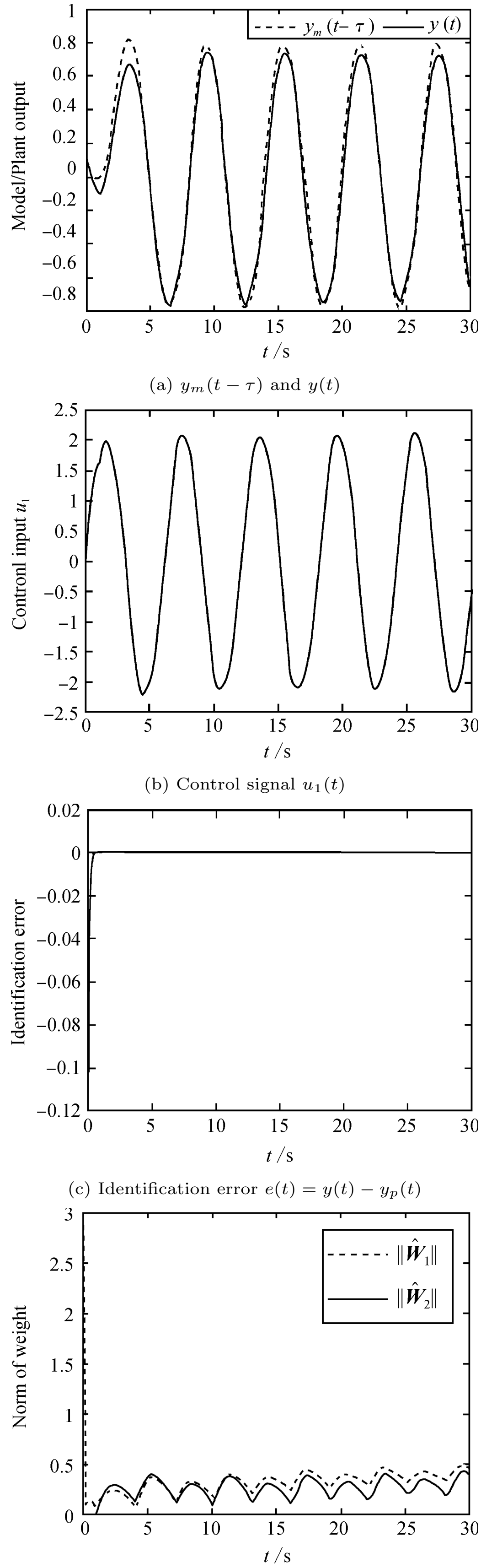
$$y(s) = \frac{2.5\mathrm{e}^{-15s}}{(20s+1)(60s+1)}u(s) \tag{49}$$

Since $g(\bar{\boldsymbol{x}})$ in system (49) is known, only one HONN $\hat{\boldsymbol{W}}_1^{\mathrm{T}}\boldsymbol{\Phi}_1(\boldsymbol{x}(t))$ is needed for identification. The sampling interval is 0.1 s. The reference input is a square-wave with the amplitude of 1 and the period of 120. The desired reference model is selected as (47), which means the desired trajectory $y_m(t-\tau)$ in ATPFC is a square-wave with the same amplitude and period. The control parameters are appropriately chosen as $F_1 = K_e = k_v = 1, \quad \lambda_1 = 2$; and the filter polynomial is $M(s) = 0.1s^2 + 2s + 2$. The performance of the nonlinear IMC with feedback compensation[6] (IMC-FC) for CMS (49) with the controller parameters $\alpha_1 = \alpha_2 = \beta = 10$ is discussed for comparison.

It should be noted that for the IMC-FC structure proposed in [6], the internal model of (49) must be known. However, in ATPFC, the dynamics of CMS is not required beforehand. In this simulation, the hybrid sinusoidal disturbance $d(t)$ is added to both control schemes, which aims to evaluate their robust performance.

The disturbance is set at $d(t) = 0.01(\sin 0.2\pi t + \cos 10\pi t)$ firstly. Fig. 3 (a) shows the corresponding performance. It can be seen that tracking performances of the two control schemes are all satisfactory due to their disturbance rejection capabilities. However, since the ATPFC can identify and compensate unknown nonlinear dynamics of the system on-line, smaller tracking error is obtained than that of IMC-FC. In practice, if the modeling error is large (i.e. the amplitude of unmeasured disturbance increases), the performance of IMC-FC will deteriorate due to the inappropriate internal model. As shown in Fig. 3 (b), with the disturbance $d(t) = 0.1(\sin 0.2\pi t + \cos 10\pi t)$, the performance of ATPFC is maintained and satisfactory, while IMC-FC provides an oscillatory or even unstable response. The reason is that the unmeasured disturbance $d(t)$ can be considered as a modeling error, and thus, there exists large modeling uncertainty in the control systems. For ATPFC, the NN-based linearization compensation can deal with the unknown system modeling error. The results in Fig. 3 indicate that the ATPFC possesses an excellent robust and adaptive characteristic, even though the system dynamics is unknown.

From the above simulation results, one may conclude that the proposed adaptive time-delay positive feedback control scheme can achieve fairly good control performance and has strong robust capability for unknown nonlinear affine time-delay system. The good transient tracking performance can be guaranteed while the tracking error, the identification error, and the control signal are all bounded.



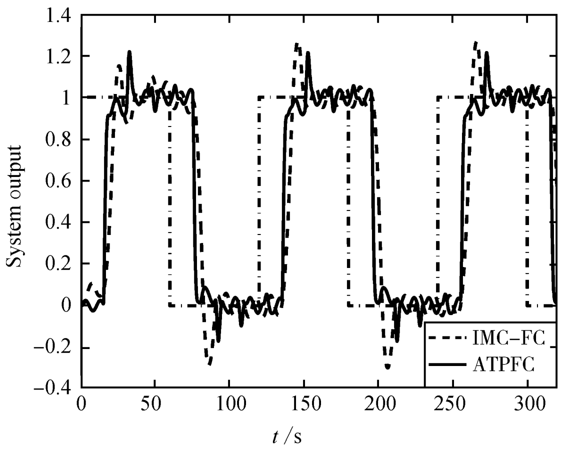
(a) $y_m(t-\tau)$ and $y(t)$

(b) Control signal $u_1(t)$

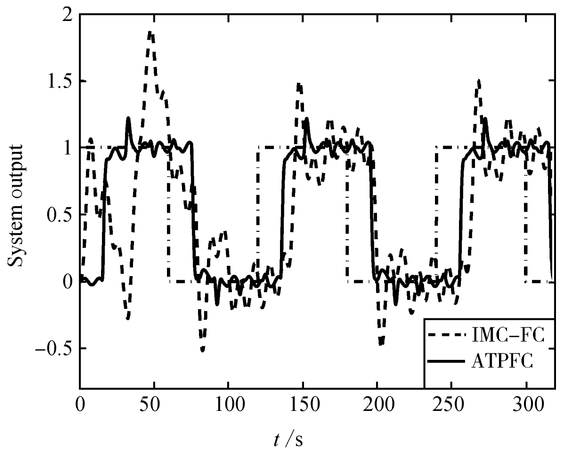
(c) Identification error $e(t) = y(t) - y_p(t)$

(d) $\|\hat{\boldsymbol{W}}_1\|$ and $\|\hat{\boldsymbol{W}}_2\|$

Fig. 2 Identification and control performance for (46)



(a) Output tracking with $d(t) = 0.01(\sin 2\pi t + \cos 10\pi t)$



(b) Output tracking with $d(t) = 0.1(\sin 2\pi t + \cos 10\pi t)$

Fig. 3 Control performance for (49)

5 Conclusion

In this paper, a novel time-delay positive feedback controller with adaptive identification and compensation is investigated for a class of unknown affine nonlinear systems with input time-delay. The high-order neural networks with adaptive updating laws are used to identify the unknown time-delay system. The time-delay positive feedback controller is developed based on the neural network linearization compensation. The system can track the delayed trajectory of a desired reference model with a small residual error around the origin. The stability of the closed-loop system, boundedness of the identification error and tracking error are all proved based on Lyaponuv theorem. Simulation results verify the validity of our theoretical analysis through the practical implementations of the proposed scheme for unknown time-delay systems.

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