The Fifteenth International Symposium on Artificial Life and Robotics 2010 (AROB 15th '10),
B-Con Plaza, Beppu,Oita, Japan, February 4-6, 2010

Adaptive Identification and Prediction Control for Time Delay Nonlinear Systems Based on Neural Networks

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Abstract: This paper presents the identification, prediction and control design for nonlinear strict-feedback systems with an input time-delay. The system is firstly transformed into a normal form by defining new state variables. A dynamical identification with a neural network (NN) is proposed to estimate the system states. The predictive NN weights are obtained without iterative calculations and utilized in constructing the adaptive predictor. Feedback control design using the predictive states is finally studied. Simulations are included to validate the effectiveness of the proposed method.

***Keywords*:** Time-delay systems, state observer, nonlinear predictor, neural networks

I. INTRODUCTION

The control design for systems with input time-delay has been widely studied, e.g. [1-5] and references therein. For linear systems, the Smith predictor [1], sliding mode control [2] and dead time compensator [3] have been validated theoretically and practically. To deal with unknown nonlinearities, neural controllers were proposed in [4] and [5] for nonlinear time-delay systems. However, the employed local linearization methodologies are inapplicable to the system, where the delay is intrinsic in the plant (e.g. fluid control, temperature control). Tan and Cauwenberghe established one-step-ahead [6] and d-step-ahead [7] predictors for nonlinear systems using neural networks. Lu and Tsai [8] proposed a neural generalized predictive control for process system. Nevertheless, these predictors mainly focus on the discrete systems, and iterative prediction calculations are required within the sample interval resulting in significant computation costs.

In this paper, we study the neural predictor and control design for strict-feedback time-delay systems without the backstepping design. The system is firstly transformed into a normal form as in [10]. A neural network is then utilized in a dynamical identification to estimate the system states, and the NN weights and their derivative can be obtained. Predictive NN weights are deduced via Taylor series expansion and used to establish the state predictor. A feedback control with the predictive states is finally constructed to achieve the tracking. The closed-loop system is guaranteed to be bounded. Compared to other NN-based predictors, the off-line learning phase, the past system information and iterative calculations are all avoided to reduce the computation costs.

II. PROBLEM STATEMENT

Consider a class of nonlinear systems with an input time-delay as

$$\begin{cases} \dot{x}_i(t) = f_i(\bar{x}_i) + g_i x_{i+1}(t), \ 1 \le i \le n-1 \\ \dot{x}_n(t) = f_n(x) + g_n u(t-\tau) \\ y(t) = x_1(t) \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1, x_2 \cdots x_i]^T \in \mathbb{R}^i, i = 1, \cdots n$, $x = [x_1, x_2 \cdots x_n]^T \in \mathbb{R}^n$, $y(t) \in \mathbb{R}$ and $u(t) \in \mathbb{R}$ are state variables, the output and input, respectively; $f_i(\bullet), i = 1, \cdots n$ are unknown but smooth nonlinear functions, $g_i, i = 1, \cdots n$ are known constant gains, and τ is a constant input delay.

The objective of this paper is to find a control $u(t)$, such that the output $y(t)$ tracks a desired trajectory $y_d(t)$. Inspired by [10], we can transform system (1) into a normal form by redefining the state variables as

$$\begin{cases} z_1 = x_1 \\ z_i = \dot{z}_{i-1}, i = 2, \cdots, n \end{cases} \tag{2}$$

Then we have $z_2 = \dot{z}_1 = f_1(x_1) + g_1 x_2$ and

$$\begin{aligned} \dot{z}_2 = \ddot{z}_1 &= \frac{\partial f_1(x_1)}{\partial x_1}\left(f_1(x_1) + g_1 x_2 \right) + g_1 \left(f_2(\bar{x}_2) + g_2 x_3 \right) \\ &= \alpha_2(\bar{x}_2) + \beta_2 x_3 \end{aligned} \tag{3}$$

where $\alpha_2(\bar{x}_2) = \left(\partial f_1(x_1)/\partial x_1\right)\left(f_1(x_1) + g_1 x_2\right) + g_1 f_2(\bar{x}_2)$ is an unknown function and $\beta_2 = g_1 g_2$ is a known constant.

Similar to (3), for $i = 3, \cdots, n-1$, we can obtain that

$$\begin{aligned} \dot{z}_i = \ddot{z}_{i-1} &= \frac{\partial \alpha_{i-1}(\bar{x}_{i-1})}{\partial \bar{x}_{i-1}} \dot{\bar{x}}_{i-1} + \beta_{i-1} \dot{x}_i \\ &= \alpha_i(\bar{x}_i) + \beta_i x_{i+1} \end{aligned} \tag{4}$$

where $\alpha_i(\bar{x}_i) = \sum_{j=1}^{i-1} \partial \alpha_{i-1}(\bar{x}_{i-1}) / \partial x_j \left(f_j(\bar{x}_j) + g_1 x_{j+1} \right) + \beta_{i-1} f_i(\bar{x}_i)$ is unknown, and $\beta_i = \beta_{i-1} g_i = \prod_{j=1}^{i} g_j$ is a known constant.

Finally, for $i = n$, we have

$$\begin{aligned} \dot{z}_n = \ddot{z}_{n-1} &= \frac{\partial \alpha_{n-1}(\bar{x}_{n-1})}{\partial \bar{x}_{n-1}} \dot{\bar{x}}_{n-1} + \beta_{n-1} \dot{x}_n \\ &= \alpha_n(x) + \beta_n u(t-\tau) \end{aligned} \tag{5}$$

where $\alpha_n(x_n) = \sum_{j=1}^{n-1} \partial \alpha_{n-1}(\bar{x}_{n-1}) / \partial \bar{x}_{n-1} \left(f_j(\bar{x}_j) + g_j x_{j+1} \right) + \beta_{n-1} f_n(x)$

This work is supported by National Natural Science Foundation of China under grant No. 60974046.

is an unknown function and $\beta_n = \beta_{n-1} g_n = \prod_{j=1}^{n} g_j$ is a known constant.

From (2)~(5), we can rewrite system (1) as

$$\begin{cases} \dot{z}_i = z_{i+1}, \quad i = 1, \cdots, n-1 \\ \dot{z}_n = \alpha_n(x) + \beta_n u(t-\tau) \\ y = z_1 \end{cases} \quad (6)$$

As can be seen, by transforming the strict-feedback system (1) into the normal form (6) with the output $y = z_1 = x_1$, the backstepping design can be avoided. However, the newly defined states $z_i, i = 2, \cdots, n$ are unavailable since the function $\alpha_n(x)$ is unknown.

A linear parameter neural network (LPNN) [4-5] can approximate a nonlinear function on a compact set Ω as

$$Q(Z) = W^{*T}\Phi(Z) + \varepsilon, \ \forall Z \in \Omega \subset \mathbb{R}^n \quad (7)$$

with bounded weights $W^* = [w_1^*, w_2^* \cdots w_L^*]^T \in \mathbb{R}^L$ and error $\varepsilon \in \mathbb{R}$, i.e. $\|W^*\| \le W_N$, $|\varepsilon| \le \varepsilon_N^*$. $\Phi(Z) = [\Phi_1(Z), \cdots \Phi_L(Z)]^T \in \mathbb{R}^L$ is a vector with $\Phi_k(\boldsymbol{Z})$ being a sigmoid function.

III. CONTROL DESIGN

A. Identification with Neural Network

For system (6), the following identification model is developed to estimate the states $z_i, i = 2, \cdots, n$:

$$\begin{cases} \dot{\hat{z}}_i = \hat{z}_{i+1}, \quad i = 1, \cdots, n-1 \\ \dot{\hat{z}}_n = -\sum_{i=1}^{n} a_i \hat{z}_i + \hat{W}(t)\Phi(x(t)) + \beta_n u(t-\tau) \\ \hat{y} = \hat{z}_1 \end{cases} \quad (8)$$

where $\hat{z}_i, i = 1, \cdots, n$ are the estimation of z_i; the vector $\hat{W} = [\hat{w}_1, \hat{w}_2 \cdots \hat{w}_L]^T \in \mathbb{R}^L$ is the NN weights given by

$$\dot{\hat{W}}(t) = F\left(\tilde{y}(t)\Phi(x(t)) - k_e \hat{W}(t)\right) \quad (9)$$

with the parameters $F = F^T > 0$, $k_e > 0$, and $\tilde{y} = y - \hat{y}$ is the output measurement error.

We can select appropriate positive parameters $a_1, \cdots a_n$ such that following matrix A is Hurwitz

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ & \ddots & \ddots & & \vdots \\ \vdots & & \ddots & \ddots & 0 \\ & & & 0 & 1 \\ -a_1 & -a_2 & \cdots & \cdots & -a_n \end{bmatrix} \in \mathbb{R}^{n \times n}, B = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} \in \mathbb{R}^n, C = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \in \mathbb{R}^n.$$

and $A^T P + PA = -Q$ and $PB = C$ hold for symmetric positive definite matrices P and Q.

Define the identification error as $\tilde{x}(t) = z(t) - \hat{z}(t)$, the NN weight error as $\tilde{W} = W^* - \hat{W}$, and apply the NN approximation (7) on the unknown nonlinear function $\varphi(x) = \alpha_n(x) + \sum_{i=1}^{n} a_i z_i(t)$, then we can get the error equation from (6) and (8) as

$$\begin{cases} \dot{\tilde{x}}(t) = A\tilde{x}(t) + B\tilde{W}^T(t)\Phi(x(t)) + B\varepsilon \\ \tilde{y} = C\tilde{x}(t) \end{cases} \quad (10)$$

B. Adaptive Predictor

In identification (8), the NN weights $\hat{w}_i(t); i = 1, \cdots n$ contain the time-varying system information. Therefore, the following adaptive predictor can be proposed:

$$\begin{cases} \dot{x}_{pi}(t+\tau) = x_{p(i+1)}(t+\tau), \quad i = 1, \cdots, n-1 \\ \dot{x}_{pn}(t+\tau) = -\sum_{i=1}^{n} a_i x_{pi}(t+\tau) + \hat{W}^T(t+\tau)\Phi(x_p(t+\tau)) + \beta_n u(t) \\ y_p(t+\tau) = C^T x_p(t+\tau) \end{cases} \quad (11)$$

where $x_p(t+\tau) = [x_{p1}(t+\tau), x_{p2}(t+\tau) \cdots x_{pn}(t+\tau)]^T \in \mathbb{R}^n$, $y_p(t+\tau) \in \mathbb{R}$ are the predictions of future states and the output, and $\hat{W}(t+\tau) \in \mathbb{R}^L$ denotes the predictive NN weights, which can be given as

$$\hat{W}(t+\tau) = \hat{W}(t) + \tau\dot{\hat{W}}(t) \quad (12)$$

Define the prediction error as $\tilde{x}_p(t) = z(t+\tau) - x_p(t+\tau)$, then from predictor (11) and system (6), one can obtain

$$\begin{aligned} \dot{\tilde{x}}_p(t) = A\tilde{x}_p(t) + B[&W^{*T}(t+\tau)\Phi(x(t+\tau)) \\ &- \hat{W}^T(t+\tau)\Phi(x_p(t+\tau))] + B\varepsilon \end{aligned} \quad (13)$$

C. Control Design

Denote $x_d(t) = [y_d, \dot{y}_d, \cdots y_d^{(n-1)}]^T$ as the reference trajectory, then the control error and the filtered error between $x_p(t+\tau)$ and $x_d(t)$ can be given as

$$E(t) = x_p(t+\tau) - x_d(t), \ \delta(t) = [\bar{\lambda}^T \ \ 1]E(t) \quad (14)$$

with $\bar{\lambda} = [\lambda_1, \lambda_2 \cdots \lambda_{n-1}]^T$ an appropriate vector, such that $s^{n-1} + \lambda_{n-1}s^{n-2} + \cdots \lambda_1$ is Hurwitz.

We can design the feedback control $u(t)$ as

$$\begin{aligned} u(t) = \frac{1}{\beta_n}\Big\{&-k_r\delta(t) + y_d^{(n)}(t) - [0 \ \ \bar{\lambda}^T]E(t) \\ &+ \sum_{i=1}^{n} a_i x_{pi}(t+\tau) - \hat{W}^T(t+\tau)\Phi(x_p(t+\tau))\Big\} \end{aligned} \quad (15)$$

where $k_r > 0$ is a positive control parameter.

Remark 1. During each sample interval, the NN weights $\hat{W}(t)$ and $\dot{\hat{W}}(t)$ in the identification (8) are obtained according to (9). Then $\hat{W}(t)$ and $\dot{\hat{W}}(t)$ are utilized in the predictor (11) to obtain the predictive weights $\hat{W}(t+\tau)$. Finally, the predictive states $x_p(t+\tau)$ and the term $\hat{W}^T(t+\tau)\Phi(x_p(t+\tau))$ are employed in the controller (15) to deduce the control $u(t)$.

D. Stability Analysis

We have the following results:

Theorem 1. Consider the time-delay system (1) with the identification (8), the predictor (11) and the controller (15), then all signals in the closed-loop system are bounded. Moreover, the tracking error $\vartheta(t)=x(t+\tau)-x_d(t)$ is also bounded.

Proof: It is known that the NN basis function $\Phi(x)$ is bounded, i.e. $\|\Phi(x)\|\le\Phi_M$ and $\|\Phi(x)-\Phi(x_p)\|\le\Phi_X$ with positive constants $\Phi_M\ge 0$, $\Phi_X\ge 0$. We first select a Lyapunov function as $V_1=\frac{1}{2}\hat{W}^T F^{-1}\hat{W}$, then the derivative of V_1 along (9) can be given as

$$\begin{aligned}\dot{V}_1 &= \hat{W}^T F^{-1}\dot{\hat{W}} = \tilde{y}\hat{W}^T\Phi(x)-k_e\hat{W}^T\hat{W}\\ &\le -\left\|\hat{W}\right\|(k_e\left\|\hat{W}\right\|-\lambda_M(C)\Phi_M\left\|\tilde{x}\right\|)\end{aligned} \tag{16}$$

Then according to Lyapunov theorem, it is known that $\hat{W}$ is bounded by $\left\|\hat{W}\right\|\le\lambda_M(C)\Phi_M\left\|\tilde{x}\right\|/k_e$.

Furthermore, from (9) and (12), we get

$$\begin{aligned}\left\|\dot{\hat{W}}\right\| &\le \lambda_M(C)\lambda_M(F)\Phi_M\left\|\tilde{x}\right\|+k_e\lambda_M(F)\left\|\hat{W}\right\|\\ &\le 2\lambda_M(C)\lambda_M(F)\Phi_M\left\|\tilde{x}\right\|\end{aligned} \tag{17}$$

and

$$\begin{aligned}\left\|\hat{W}(t+\tau)\right\| &\le \left\|\hat{W}\right\|+\tau\left\|\dot{\hat{W}}\right\|\\ &\le[\lambda_M(C)\Phi_M/k_e+2\tau\lambda_M(C)\lambda_M(F)\Phi_M]\left\|\tilde{x}\right\|\end{aligned} \tag{18}$$

Then select the Lyapunov function as

$$V=V_2+V_3=\frac{1}{2}\tilde{x}_p^T P\tilde{x}_p+\frac{1}{2}\tilde{x}^T P\tilde{x}+\frac{1}{2}\tilde{W}^T F^{-1}\tilde{W}+\frac{1}{2}\delta^2 \tag{19}$$

Differentiating $V_2=\frac{1}{2}\tilde{x}_p^T P\tilde{x}_p+\frac{1}{2}\tilde{x}^T P\tilde{x}+\frac{1}{2}\tilde{W}^T F^{-1}\tilde{W}$ along (9), (10) and (13), it follows

$$\begin{aligned}\dot{V}_2 = &-\frac{1}{2}\tilde{x}_p^T Q\tilde{x}_p+\tilde{x}_p^T PB\{W^{*T}(t+\tau)\Phi(x(t+\tau))\\ &-\hat{W}^T(t+\tau)\Phi(x_p(t+\tau))\}+\tilde{x}_p^T PB\varepsilon-\frac{1}{2}\tilde{x}^T Q\tilde{x}\\ &+\tilde{x}^T PB\tilde{W}^T\Phi(x)+\tilde{x}^T PB\varepsilon+\tilde{W}^T F^{-1}F(-\tilde{y}\Phi(x)+k_e\hat{W})\end{aligned} \tag{20}$$

From (18), we can get

$$\begin{aligned}&\|W^{*T}(t+\tau)\Phi(x(t+\tau)-\hat{W}^T(t+\tau)\Phi(x_p(t+\tau))\ \|\\ &=\|\tilde{W}^T(t+\tau)\Phi(x(t+\tau))+\hat{W}^T(t+\tau)[\Phi(x(t+\tau))-\Phi(x_p(t+\tau))]\|\\ &\le\Phi_M W_N+(\Phi_X+\Phi_M)\|\hat{W}(t+\tau)\|\le C_1+C_2\|\tilde{x}\|\end{aligned} \tag{21}$$

where $C_1=\Phi_M W_N$, $C_2=[2\tau\lambda_M(C)\lambda_M(F)\Phi_M+\lambda_M(C)\Phi_M/k_e](\Phi_X+\Phi_M)$ are positive constants.

Moreover, consider $\tilde{W}^T\hat{W}=\tilde{W}^T(W^*-\tilde{W})\le-\frac{1}{2}\|\tilde{W}\|^2+\frac{1}{2}W_N^2$ and $ab\le(a^2+k^2b^2)/2k$ with $k>0$, we have

$$\begin{aligned}\dot{V}_2\le&-\frac{1}{2}[\lambda_m(Q)-\frac{1}{k}-\lambda_M(P)C_2]\|\tilde{x}_p\|^2+\frac{k}{2}[\lambda_M(P)(C_1+\varepsilon_N)]^2\\ &-\frac{1}{2}[\lambda_m(Q)-\frac{1}{k}-\lambda_M(P)C_2]\|\tilde{x}\|^2+\frac{k}{2}[\lambda_M(P)\varepsilon_N]^2-\frac{1}{2}k_e\|\tilde{W}\|^2+\frac{1}{2}k_eW_N^2\end{aligned} \tag{22}$$

On the other hand, taking the time derivative of $V_3=\delta^2/2$ along (14) and (15), it can yield

$$\dot{V}_3=\delta\dot{\delta}\le-k_r\delta^2 \tag{23}$$

Then from (22) and (23), it can be deduced that

$$\dot{V}=\dot{V}_2+\dot{V}_3\le-\overline{\beta}\overline{V}+D \tag{24}$$

where $D=[k\lambda_M^2(P)(C_1^2+2\varepsilon_N C_1+2\varepsilon_N^2)+k_eW_N^2]/2$ and $\overline{\beta}=\min\{(\lambda_m(Q)-1/k-\lambda_M(P)C_2)/\lambda_M(P),\ k_e/\lambda_M(F^{-1}),2k_r\}$.

According to Lyapunov theorem, the filtered error δ, the identification error $\tilde{x}$, the prediction error $\tilde{x}_p$ and the NN weight error $\tilde{W}$ are all bounded. Furthermore, the control error E is also bounded according to (14). Thus, the boundedness of NN weights $\hat{W}(t)$, $\dot{\hat{W}}(t)$, $\hat{W}(t+\tau)$ and system states $\hat{x}(t)$, $x_p(t+\tau)$ are guaranteed. Consequently, the control $u(t)$ in (15) is also bounded.

Finally, the tracking error between the system states $x(t+\tau)$ and the reference trajectory $x_d(t)$ is

$$\begin{aligned}\vartheta(t)&=x(t+\tau)-x_d(t)=x(t+\tau)-x_p(t+\tau)\\ &\quad+x_p(t+\tau)-x_d(t)=\tilde{x}_p(t)+E(t)\end{aligned} \tag{25}$$

then we know $\lim_{t\to\infty}\|\vartheta(t)\|=\lim_{t\to\infty}\|\tilde{x}_p(t)+E(t)\|\le\lim_{t\to\infty}\|\tilde{x}_p\|+\lim_{t\to\infty}\|E\|$, which implies that the closed-loop tracking error $\vartheta(t)$ is also bounded. □

IV. SIMULATION

Example 1: Consider the following nonlinear system

$$\begin{cases}\dot{x}_1(t)=x_2(t)+0.5x_1^2(t)\\ \dot{x}_2(t)=0.2(1-x_1^2(t))x_2(t)-x_1(t)\sin(x_2(t))+u(t-\tau)\\ y(t)=x_1(t)\end{cases} \tag{26}$$

The reference signal is specified as $y_d(t)=\sin(0.2\pi t)$. The simulation parameters are set as $a_1=6$; $a_2=1$, $\lambda_1=1$, $k_r=1$, $\Phi(x)=2/(1+e^{-0.5x})+3$, $F=diag(20,\cdots,20)$ and $k_e=5$. The initial conditions are $x_i(0)=\hat{x}_i(0)=x_{pi}(0)=0$ and $\hat{W}(0)=[0,\cdots,0]^T$.

The tracking response of the controlled system with a time-delay $\tau=0.3$ s is depicted in Fig.1. The top figure is the system output $y(t)$ and the reference $y_d(t)$. The profile of system states $x_1(t)$, $x_2(t)$ and the control signal $u(t)$ are provided in the middle and the bottom. As can be seen, the control and system states are all bounded. Moreover, the satisfactory tracking performance is achieved since the effect of input time-delay and unknown nonlinearities can be compensated effectively by the proposed method.

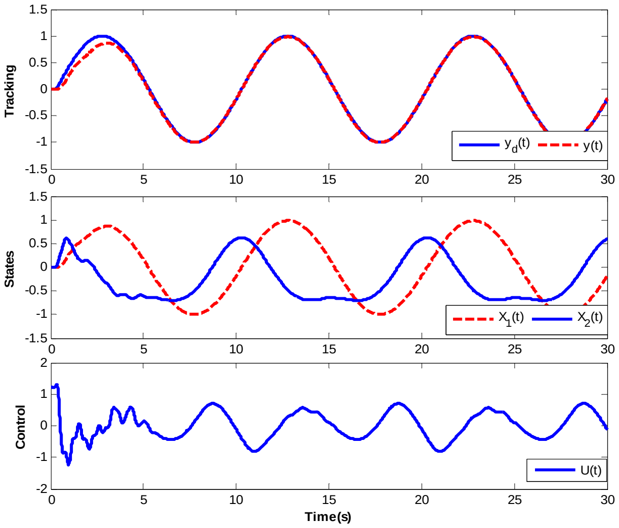

Fig.1 Control performance

Example 2: To further verify the proposed method, the following system as in [11] is utilized without the state delay term

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -3x_1 - 2x_2 + 0.5x_1\sin(x_2) + \sin(60\pi t) + u(t-\tau) \\ y = x_1 \end{cases} \quad (27)$$

In this example, the reference signal is selected as $y_d(t) = 0$. The initial system conditions are chosen as $x_1(0) = -1.6; x_2(0) = 1$. In simulation, the parameters are specified as $a_1 = 3$; $a_2 = 2$, $\lambda_1 = 10$, $k_r = 10$, and the parameters of NN identification and predictor are given as $\Phi(x) = 2/(1+e^{-0.1x}) - 0.5$, $F = diag(0.2,\cdots,0.2)$, $k_e = 5$. The initial conditions are chosen as $\hat{x}_i(0) = x_{pi}(0) = 0$ and $\hat{W}(0) = [0,\cdots,0]^T$.

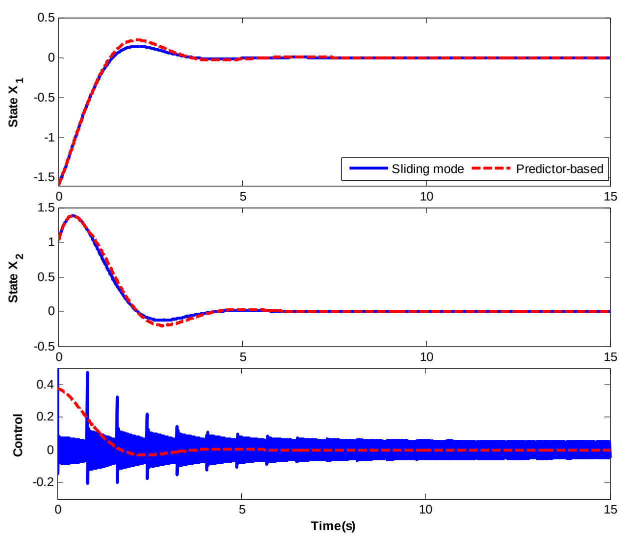

Fig.2 Comparative control performance

For comparison, the sliding model control presented in [11] is also provided. The system states under different controllers and the corresponding control signals are depicted in Fig.2. It is shown that both the sliding mode control and the proposed predictor-based control can guarantee the convergence of system states. However, the control signal of the predictor-based method is smoother than that of the sliding mode scheme.

V. CONCLUSION

A novel neural adaptive nonlinear state predictor is developed in this paper. The predictive NN weights can be obtained from the NN weights in the identification via Taylor series expansion. The proposed identification, prediction and control schemes can be implemented online without recursive calculations such that the computational costs can be reduced. Moreover, strict-feedback systems are transformed into a class of normal systems such that the backstepping design can be avoided in the control design.

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