Simplified adaptive neural control of strict-feedback nonlinear systems

Yongping Pan, Yiqi Liu, Haoyong Yu

Abstract

This paper presents a simplified adaptive backstepping neural network control (ABNNC) strategy for a general class of uncertain strict-feedback nonlinear systems. In the backstepping design, all unknown functions at intermediate steps are passed down such that only a single neural network is needed to approximate a lumped uncertainty at the last step. The closed-loop system achieves practical asymptotic stability in the sense that all involved signals are bounded and the tracking error converges to a small neighborhood of zero. The contribution of this study is that the complexity growing problem of the traditional ABNNC design is substantially eliminated for a general class of uncertain strict-feedback nonlinear systems, where the constraints of control parameters that guarantee closed-loop stability is clearly demonstrated. An illustrative example has verified effectiveness of our approach.

Keywords:
Adaptive control
Backstepping
Neural network
Function approximation
Strict-feedback
Nonlinear system

1. Introduction

Adaptive approximation-based control using fuzzy systems or neural networks (NNs) has attracted great concern due to its effectiveness of modeling functional uncertainties in nonlinear systems [1]. Some recent results can be referred to [2–12]. The most prominent benefit of applying fuzzy or NN approximation during control synthesis is that the difficulty of system modeling in many practical control problems can be largely alleviated. By the combination of backstepping design and function approximation, adaptive backstepping NN control (ABNNC) has also been developed for some classes of strict-feedback nonlinear systems (SFNSs) with mismatched uncertainties [13–19]. A general class of SFNSs can be expressed as follows:

\[
\begin{aligned}
\dot{x}_i &= f_i(x) + g_i(x)x_{i+1} \\
& \quad (i = 1, 2, \ldots, n - 1) \\
x_n &= f_n(x_n) + g_n(x_n)u \\
y &= x_1 
\end{aligned}
\] (1)

where \(x_i(t) = [x_1(t), x_2(t), \ldots, x_i(t)]^T \in \mathbb{R}^i\) are plant states, \(u(t) \in \mathbb{R}\) and \(y(t) \in \mathbb{R}\) are the control input and the controlled output, respectively. \(f_i(x) : \mathbb{R}^i \rightarrow \mathbb{R}\) are nonlinear driving functions, \(g_i(x) : \mathbb{R}^i \rightarrow \mathbb{R}\) are control gain functions (i.e., affine terms), and \(i = 1, 2, \ldots, n\). In the conventional ABNNC design, the controller complexity grows drastically as the plant order increases owing to two reasons: one is the repeated derivations of virtual control inputs, and the other is the application of multiple approximators.

To avoid the repeated derivations, a dynamic surface control technique that applies a first-order filter at each backstepping step can be combined to the ABNNC design [20–24]. Yet in this technique, at least \(n\) NNs are still needed for an \(n\)-th-order system. To completely eliminate the complexity growing problem, single NN approximation-based ABNNC was proposed for a special class of uncertain SFNS of (1) with \(g_i(x) = 1\) \((i = 1, 2, \ldots, n)\) in [25]. The key idea in this approach is that all unknown functions at intermediate steps are passed down during backstepping such that only one NN is needed to approximate a lumped uncertainty at the last step. This approach leads to a simple control structure which only contains an actual control law with one parameter adaptive law. However, the stability result obtained in [25] is based on a precondition that the optimal NN approximation error is bounded before control, which implies that the plant states are already bounded before control. Therefore, the stability condition in [25] still needs to be further investigated.

In this study, a single NN approximation-based ABNNC is presented for a general class of uncertain SFNSs (1), where the constraints of control parameters that guarantee closed-loop stability is clearly demonstrated. The design procedure of the proposed approach is as follows: first, during the backstepping design, all unknown functions of virtual control laws at intermediate steps are passed down to the last step; second, an ideal actual control law is proposed to guarantee closed-loop stability; third, only one radial basis function
(RBF) NN is applied to approximate a lumped uncertainty in the ideal actual control law; finally, the closed-loop system is proved to be practically asymptotically stable under sufficient constraints of control parameters depended on an initial condition of plant states.

The rest of this paper is organized as follows. The control problem is formulated in Section 2. The backstepping procedure is given in Section 3. The proposed approach is provided in Section 4. An illustrative example is given in Section 5. Finally, conclusions are summarized in Section 6. Throughout this paper, $\mathbb{R}$, $\mathbb{R}^+$ and $\mathbb{R}^-$ denote the spaces of real numbers, positive real numbers and real $n$-vectors, respectively, and $\cdot | \cdot$, $\cdot \parallel \cdot \parallel _{\cdot}$ denote the absolute value, 2-norm and $\infty$-norm, respectively, $L_2$ and $L_{\infty}$ denote the spaces of square integrable signals and essentially bounded signals, respectively, $\min \{ \cdot \}$, $\max \{ \cdot \}$ and $\sup \{ \cdot \}$ represent the functions of minimum, maximum and supremum, respectively, and $c^\alpha$ represents the space of functions whose $k$-order derivatives all exist and are continuous, where $k$ is a positive integer.

#### 2. Problem formulation

Revisit the system (1) with $f(\cdot)$ and $g_1(\cdot)$ being of $C^1$ and unknown. Let $y_d(t) \in \mathbb{R}$ be a reference signal, $y_d(t)=y_d(0)$, $y_d(2)$, $\ldots$, $y_d(t_i)$ $\in \mathbb{R}$ and $y_d(t_i)=y_d(t)$. $y_d(t)$ satisfies $y_d(t)$ with $i=2, 3, \ldots, n$. Define compact sets $\Omega_1=[x_1 \mid x_1 \leq C_0]$, $\Omega_2=[x_1 \mid x_1 \leq C_0]$, and $\Omega_{\infty}=[y_d \mid y_d \leq C_0]$, where $C_0 \in \mathbb{R}$ are constants and $C_0 \leq C_0$. The following assumptions are exploited in the subsequent development.

**Assumption 1.** There exist constants $g_0, g_1 \in \mathbb{R}^+$ such that $0 < g_0 \leq \|y_1(t)\| \leq g_1$, with $i=1, 2, \ldots, n$. Without loss of generality, it is assumed that $g_1(t) > 0$.

**Assumption 2.** The reference signal $y_d(t)$ satisfies $y_d(t) \in \Omega_{\infty}$ for $i=1, 2, \ldots, n+1$.

Define $k_0^i=1$ and $k_i^j=k_{i-1} \cdots k_{i-j+1}$, $j \leq i$ for $j \geq 1$, where $k_i \in \mathbb{R}^+$ with $i=1, 2, \ldots$, $i$ is a constant control gains, $i$ is a positive integer, and $j$ is a nonnegative integer. The notation $k_i^j=k_i^{j-i}$ is frequently used in the subsequent control design. The control objective of this study is to develop an NN-based control strategy for the system (1) under Assumptions 1 and 2 such that the system output $y$ tracks its desired signal $y_d$ as accurate as possible.

**Remark 1.** The approach in [25] considers the system in (1) under an assumption that $g_1(i)=1$ ($i=1, 2, \ldots, n$). Differing from [25], this study focuses on a general class of SFNs (1) without this strict assumption. In Assumption 1, the controllability condition $|y_d| > 0$ can be found in all existing ABNNC approaches, and the locally bounded condition $0 < g_0 \leq \|y_d(t)\| \leq g_1$, for $x \in \Omega_4$, can be naturally obtained by $f(\cdot)$ and $g_1(\cdot)$ being of $C^1$.

#### 3. Backstepping design

Define the output tracking error $z_1(t)=y-d(t)$ and virtual tracking errors $z_i(t)=x(t)-x_i(t)$ with $i=2, 3, \ldots, n$, where $x_i$ is a virtual control inputs defined later. Let $\mathbf{x}=[x_1^T, y_d(t), x_{i+1}^T]^T$ with $i=2, 3, \ldots, n$. The procedure of backstepping design is as follows.

**Step 1.** The derivative of $z_1$ is as follows:

\[
\dot{z}_1 = f_1(x_1) - y_d + g_1(x_1)x_2.
\]  

Applying $x_2=\alpha_2$, and (3) to (2) yields

\[
z_2 = f_2(x_1) - z_1 \quad \text{and} \quad g_1(x_1)x_2 = \alpha_2.
\]

**Step 2.** The derivative of $z_2$ is as follows:

\[
z_2 = f_2(x_1) - z_1 \quad \text{and} \quad g_1(x_1)x_2 = \alpha_2.
\]

Applying (3) to the definition of $z_2$, one obtains

\[
z_2 = f_2(x_1) - z_1 - h_1(x_1)\quad \text{and} \quad g_1(x_1)x_2 = \alpha_2.
\]

Finally, the procedure of backstepping design is as follows.

**Step 3.** The derivative of $z_3$ is as follows:

\[
z_3 = f_3(x_1) - z_2 \quad \text{and} \quad g_1(x_1)x_2 = \alpha_2.
\]

Applying the above result to (6) leads to

\[
z_3 = f_3(x_1) - z_2 - h_2(x_2) = g_1(x_1)x_2 - \alpha_2.
\]

To compensate for the interconnected term $g_1(x_1)x_2$ in (4), a correlative interconnected term $g_1(x_1)x_2$ is added and subtracted at the right side of the above equality, which results in

\[
z_3 = f_3(x_1) + g_1(x_1)x_2 - \alpha_2 = g_1(x_1)x_2 - \alpha_2.
\]

To stabilize the subsystem in (8), where

\[
z_4 = f_4(x_1) + g_1(x_1)x_2 - \alpha_2.
\]

Applying $x_3=\alpha_3$, and (9) to (8) yields

\[
z_4 = f_4(x_1) + g_1(x_1)x_2 - \alpha_2 = g_1(x_1)x_2 - \alpha_2.
\]

Applying (9) with (5) to the definition of $z_5$, one gets

\[
z_5 = f_5(x_1) + g_1(x_1)x_2 - \alpha_2 = g_1(x_1)x_2 - \alpha_2.
\]

Adding and subtracting $g_1(x_1)x_2$ at the right side of the above equality leads to

\[
z_5 = f_5(x_1) + g_1(x_1)x_2 - \alpha_2 = g_1(x_1)x_2 - \alpha_2.
\]

Choosing the virtue control input

\[
\alpha_{i+1} = -k_z z_i.
\]
to stabilize the subsystem in (14), where
\[ h_i(x_{ni}) = \left( f_i(x) - g_{ni} - z_{ni} - \alpha_i(x_{ni}) \right)/g_{ni}(x). \]

Applying \( x_1 = z_1 + \alpha_1 \) and (15) to (14) yields
\[ \dot{z}_1 = g_1(x_1)(-k_1z_1 + z_{n1} - 1)z_{n1}(-1). \]  

(16)

Noting (15) and (11), one obtains
\[ z_i = \sum_{j=1}^{i} k_{ij}^{-1}(x_j - y_d) + \sum_{j=1}^{i} k_{ij}^{-1}h_j^*(x_j). \]  

(17)

where \( h_j^*(x_{ni}) = h_j(x_{ni}) + y_d(j). \)

Step N: The derivative of \( z_n \) is as follows:
\[ \dot{z}_n = f_n(x_n) + g_{n-1}(x_{n-1})u - \alpha_n \]

(18)

where \( \alpha_n \) is given by
\[ \alpha_n = (\partial \alpha_n/\partial x_n^T)z_{n-1} + (\partial \alpha_n/\partial y_d)y_{dn} = \alpha_i^*(x_n). \]  

(19)

Then, (18) can be rewritten as
\[ \dot{z}_n = f_n(x_n) + g_{n-1}(x_{n-1})u - \alpha_i^*(x_n) \]

Adding and subtracting \( g_{n-1}(x_{n-1})z_{n-1} \) at the right side of the above equality leads to
\[ \dot{z}_n = f_n(x_n) + g_{n-1}(x_{n-1})z_{n-1} - \alpha_i^*(x_n) + g_{n-1}(x_{n-1})u - g_{n-1}(x_{n-1})z_{n-1}. \]  

(20)

Design an ideal actual control law
\[ u^*(x_{ni}) = -k_0z_0 - h_0(x_{ni}) \]

(21)

to stabilize the last subsystem in (20), where
\[ h_0(x_{ni}) = (f_0(x_0) + g_{n-1}(x_{n-1})z_{n-1} - \alpha_i^*(x_{ni}))/g_{n-1}(x_{ni}). \]

Applying (15) with (17) to the definition of \( z_n \), one gets
\[ z_n = \sum_{j=1}^{n} k_{nj}^{-1}(x_j - y_d) + \sum_{j=1}^{n} k_{nj}^{-1}h_j^*(x_j). \]  

(22)

Now, choose a Lyapunov function candidate
\[ V_2(z) = \sum_{i=1}^{n} z_i^2/2 \]  

(23)

with \( z = [z_1, z_2, \ldots, z_n]^T \) for the entire system composed of (4), (10), (16) and (20). The following lemma shows the stability result of the closed-loop system under known plant dynamics.

**Lemma 1.** **For the system (1) satisfying Assumptions 1 and 2, if the actual control law is chosen as \( u = u^* \) in (21), then the closed-loop system achieves exponential stability in the sense of \( \lim_{t \to \infty} \| z(t) \| = 0 \).**

**Proof.** Differentiating \( V_2 \) in (23) with respect to time \( t \) and applying (4), (10), (16) and (21), one gets
\[ V_2 = -k_1g_1(x_1)z_1^2 + z_1z_2g_1(x_1) \]
\[ -k_2g_2(x_2)z_2^2 + z_2z_3g_2(x_2) - z_1z_2g_1(x_1) \]
\[ \vdots \]
\[ -k_{n-1}g_{n-1}(x_{n-1})z_{n-1}^2 + z_{n-1}z_ng_{n-1}(x_{n-1}) - z_{n-2}z_{n-1}g_{n-2}(x_{n-2}). \]
\[ -k_ng_{n}(x_{n})z_n^2 + z_nz_{n+1}g_{n}(x_{n+1}). \]

Thus, it is easy to obtain
\[ \dot{V}_2 = -\sum_{i=1}^{n} k_i g_i z_i^2 \leq -k V_2 \leq 0 \]

with \( k_i = \min(2k_{gi}, i = 1, 2, \ldots, n) \in \mathbb{R}^+ \), where all the interconnected terms \( z_{ni}z_{ni} \) with \( i = 1, 2, \ldots, n \) are completely compensated. The above result implies that the closed-loop system achieves exponential stability in the sense of \( \lim_{t \to \infty} \| z(t) \| = 0 \).  

**4. Adaptive neural network control**

The ideal actual control law \( u^* \) in (21) is unreliable due to the unknown plant functions \( f_1(z) \) and \( g_i(z) \) \( i = 1, 2, \ldots, n \). From the definitions of \( \alpha_i^* \) in (5), (13) and (19), \( \alpha_i^* \) are of class \( C^1 \) with respect to there variables, where \( i = 2, 3, \ldots, n \). Since \( f_1(z) \) and \( g_i(z) \) and \( \alpha_i^* \) are of class \( C^1 \), \( h_0(z) \) are of class \( C^1 \), where \( i = 1, 2, \ldots, n \). Hence, NNs can be applied to approximate certain functions depended on \( h_1(z) \) to \( h_n(z) \). To avoid NN approximation at the 1th to \( (n-1) \)th backstepping steps, the expression of \( z_n \) in (22) is substituted into (21), which results in
\[ u^* = -\sum_{j=1}^{n} k_j x_j^{-1}(x_j - y_d) - F(x_{ni}) \]

(24)

where \( F(z) \) is a lumped uncertainty defined by
\[ F(x_{ni}) = \sum_{j=1}^{n} k_j h_j^*(x_{ni}) \]

(25)

in which \( h_j^*(x_{ni}) = h_j(x_{ni}) \). Next, a class \( C^1 \) linearly parameterized RBF NN as follows [1]:
\[ \hat{F}(x_{ni}, \hat{W}) = \hat{W}^T \Phi(x_{ni}) \]

(26)

is applied to approximate \( F(z) \) in (25), where \( \Phi_1(z) \) : \( \mathbb{R}^2 \rightarrow \mathbb{R}^M \) satisfying \( ||\Phi(z)|| \leq \psi \) is the vector of basis functions, \( W \in \mathbb{R}^M \) is the vector of adjustable weights, \( \psi \in \mathbb{R}^+ \) is a certain constant, and \( M \) is the number of NN nodes. Then, a certain actual control law can be determined as follows:
\[ u = -\sum_{j=1}^{n} k_j x_j^{-1}(x_j - y_d) - \hat{F}(x_{ni}, \hat{W}). \]

(27)

Define compact sets \( \Omega_c = \{ W \mid \| W \| \leq \psi_c \}, \Omega_{ce} = \{ x_{ni} \mid x_{ni} \in \Omega_c, y_{dn} \in \Omega_{de} \} \) where \( \psi_c \in \mathbb{R}^+ \) is a constant. Next, define an optimal NN approximation error \( \varepsilon \) as follows:
\[ \varepsilon(x_{ni}) = F(x_{ni}) - \hat{F}(x_{ni}, \hat{W}). \]

(28)

where \( W^* \) is a vector of optimal weights given by
\[ W^* = \arg \min_{W \in \Omega_c} \left( \sup_{x_{ni} \in \Omega_c} || F(x_{ni}) - \hat{F}(x_{ni}, \hat{W}) || \right). \]

From the universal approximation property of NNs [1], one has the following lemma.

**Lemma 2.** **The optimal approximation error \( \varepsilon \) given by (28) can be bounded by a certain constant \( \varepsilon = \sup_{x_{ni} \in \Omega_c} || \varepsilon(x_{ni}) || / \Omega_c \) dominated by the number of NN nodes.**

Adding and subtracting \( g_{ni}(z_0) \) at the right side of (20) and applying (21) and (20), one gets
\[ \dot{z}_n = g_n(x_{ni})(F(x_{ni}) - \hat{F}(x_{ni}, \hat{W}) - k_0z_n) - g_{n-1}(x_{n-1})z_{n-1}. \]

(29)

Noting (28), it can be shown that
\[ \dot{z}_n = g_n(x_{ni})(W^* \Phi(x_{ni}) + \varepsilon - k_0z_n) - g_{n-1}(x_{n-1})z_{n-1}. \]

in which \( W = W^* - \hat{W} \).

Choose an adaptive law of \( \hat{W} \) as follows:
\[ \dot{W} = \gamma(z_1 \Phi(x_{ni}) - \sigma W). \]

(30)
where $\gamma \in \mathbb{R}^+$ is a learning rate, and $\sigma \in \mathbb{R}^+$ is a small constant. Then, choose a Lyapunov function candidate

$$V(x, \dot{W}) = \sum_{i=1}^{n} z_i^2 / 2 + \dot{W}^T \dot{W} / 2\gamma$$

for the closed-loop system composed of (4), (10), (16), (29) and (30). The following theorem is established to demonstrate the stability result of this study.

**Theorem 1.** For the system (1) satisfying Assumptions 1 and 2 driven by the control law (27) with (26) and (30) and any given $x_n(0) \in \Omega_o$, and $W(0) \in \Omega_c$, there exist a suitably large approximation region $\Omega_c$ satisfying $\Omega_c \supset \Omega_o$, and suitably large control gains $k_i$ satisfying (33) under $\dot{x}_n \in \Omega_c$, such that the closed-loop system achieves practical asymptotic stability in the sense that all involved signals are bounded and the tracking error $z_t$ converges to a small neighborhood of 0 dominated by $\lambda$ and $k_i$ with $i = 1, 2, \ldots, n$.

**Proof.** Differentiating $V$ in (31) with respect to time $t$, applying (4), (10), (16) and (29) to resulting expression and noting the results in the proof of Lemma 1, one obtains

$$V = -\sum_{i=1}^{n} (k_i g_i - \sigma) z_i^2 / 2 + \sigma |W|^2 / 2.$$  

Applying (30) to the above expression yields

$$V = -\sum_{i=1}^{n} (k_i g_i - \sigma) z_i^2 / 2 + \sigma |W|^2 / 2.$$  

If the selection of $k_i$ makes $\dot{z}_t^2 < 0$, then

$$V < -\sum_{i=1}^{n} (k_i g_i - \sigma) z_i^2 / 2 + \sigma |W|^2 / 2.$$  

From (33) and the definition of $\sigma$, it is shown that

$$\dot{V} < -\sum_{i=1}^{n} (k_i g_i - \sigma) z_i^2 / 2 + \sigma |W|^2 / 2.$$  

Then, one obtains

$$\dot{V} < -\sum_{i=1}^{n} (k_i g_i - \sigma) z_i^2 / 2 + \sigma |W|^2 / 2.$$  

Which implies that $z_t^2 \leq \frac{\sigma}{k_t} |W|^2 / 2$, and $\dot{V} < 0$, which implies that $\dot{z}_t^2 < 0$. Thus, the stability result is established.

**Remark 2.** In the approach of [25], the stability result similar to (34) is based on a precondition that the optimal NN approximation error $\varepsilon$ in (28) is bounded inside control, which implies that $x_n$ keeps within $\Omega_c$ without control. Compared with the approach of [25], the differences of the proposed approach include: (1) a wider class of uncertain SFNs is considered; (2) the initial conditions of $x_n(0)$ and $W(0)$ are analyzed during stability proof; (3) it is demonstrated that the constraint of control gains $k_i$ is $1 \leq i \leq 2, \ldots, n$ in (33) should be satisfied under the bounds $r, g_{m0}$ and $g_{m1}$, which ensures closed-loop stability.

**Remark 3.** To ensure the reliability and safety of modern industrial processes, data-driven methods have been receiving great attention for process monitoring, fault detection and diagnosis [27–29]. The combination of ABNNC with data-driven methods is a very interesting topic. Yet, since this study focuses on ABNNC for uncertain SFNs, this topic is out of the scope but possible to be further work of this study.

## 5. An illustrative example

Consider a simple example in [14] with the following SFNS:

$$\begin{align*}
x_1 &= 0.5x_1 + (1 + 0.1t^2)x_2 \\
x_2 &= x_1x_2 + (2 + \cos x_1)y \\
y &= x_1
\end{align*}$$

and a $y_d$ generated by the Van der Pol oscillator system:

$$\begin{align*}
\dot{x}_1 &= \dot{x}_2 \\
\dot{x}_2 &= -x_1 + \beta(1 - x_1^2)x_2 \\
y_d &= x_1
\end{align*}$$

where its phase-plane trajectories approach a limit cycle under $\beta > 0$ and nonzero initial states.

The procedure of control design is as follows: First, select activation functions $f_i(x_i) = \exp(-|x_i| - 2(i - 1)^2) / 2.0^{x_i}$, and $x_n = [x_{1i}, \ldots, x_{ni}]^T$, $i = 1, 2, \ldots, 5$ to construct the vector of basis functions $\Phi(t)$ in (26); second, choose $k_1 = 20, k_2 = 10, \gamma = 5000, \sigma = 0.01$, and $W(0) = [0, 0, \ldots, 0]^T$ for the control law composed of (27) and (30); third, design a signal vector $Y_{d0}$, a filtered version of $y_d$, as $T(t) = Y_{d0}$, which avoids initial high gain at the
control input $[25]$, where $f_i(t) = \eta \exp(-\omega t) + \tau$ with $\eta = 1$, $\omega = 2$ and $\tau = 0.01$. For simulation, select $x_d(t) = [1.2, 1.0]^T$, $x_d(0) = [x_d1(0), x_d2(0)]^T = [1.5, 0.8]^T$ and $\beta = 0.2$ $[14]$. Control trajectories by the proposed approach are depicted in Fig. 1, where the controlled output $y$ tracks its desired signal $y_d$ quickly and accurately under a low-gain control input $u$. It is worth noting that the tracking performance is much better than that of the original literature $[14]$ maybe due to the simpler adjustment of control parameters in the proposed approach. It is also observed that the high-precision tracking is achieved at the cost of oscillation at the beginning of the control input $u$. To reduce control oscillation, the learning rate $\gamma$ should not be set to be too high in practice.

6. Conclusions

This paper has successfully developed a simplified ABNNC strategy for a general class of uncertain SFNSs. The proposed approach not only simplifies the control structure, but also drastically reduces implementation cost. The contributions of this study include: (1) the complexity growing problem of the traditional ABNNC design is substantially eliminated for a wider class of uncertain SFNSs; (2) the constraint of control parameters that guarantees closed-loop stability is clearly demonstrated. An illustrative example has been provided to verify effectiveness of the proposed approach.

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References


Yongping Pan received the B.Eng. degree in automation and the M.Eng. degree in control theory and control engineering from the Guangdong University of Technology, Guangzhou, China, and the Ph.D. degree in control theory and control engineering from the South China University of Technology, Guangzhou, in 2004, 2007, and 2011, respectively. From 2007 to 2008, he was a Control Engineer with the Santak Electronic Co., Eaton Group, Shenzhen, China, and the Light Engineering Co., Ltd., Guangzhou, China. From 2011 to 2013, he was a Research Fellow with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. He is currently a Research Fellow with the Department of Biomedical Engineering and the Singapore Institute for Neurotechnology (SINAPSE), National University of Singapore, Singapore. He has authored or co-authored more than 50 peer-reviewed research papers in journals and conferences. Dr. Pan is an Associate Editor of the International Journal of Fuzzy Systems, and serves as a Reviewer for some flagship journals. His current research interests include nonlinear and adaptive control, computational intelligence, and robotics and automation.

Yiqi Liu obtained his B.S. and M.S. degrees in automatic control from the Beijing University of Chemical Technology, Beijing, China, in 2006 and 2009, respectively, and his Ph.D. degree in measurement technology and automatic devices from the South China University of Technology, Guangzhou, China, in 2013. From 2011 to 2013, he was a visiting Ph.D. student at the Advanced Water Management Centre, University of Queensland, Australia. He is currently a Lecturer at the School of Automation Science and Engineering, South China University of Technology. His research interests include soft-sensor, statistical process monitoring, fault diagnosis, model predictive control and wastewater treatment.

Haoyong Yu received the B.S. and M.S. degrees in mechanical engineering from the Shanghai Jiao Tong University, Shanghai, China, and the Ph.D. degree in mechanical engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, in 1988, 1991, and 2002, respectively. He was a Principal Member of Technical Staff with the DSO National Laboratories, Singapore, until 2002. He is currently an Assistant Professor with the Department of Biomedical Engineering and a Principal Investigator with the Singapore Institute of Neurotechnology (SINAPSE), National University of Singapore, Singapore. His current research interests include medical robotics, rehabilitation engineering and assistive technologies, and system dynamics and control. Dr. Yu received the Outstanding Poster Award at the IEEE Life Sciences Grand Challenges Conference in 2013 and served on a number of IEEE Conference Committees.