Adaptive Neural Network Controller Design for a Class of Nonlinear Systems Using SPSA Algorithm

Ching-Hung Lee, *Member, IAENG*, Tsung-Min Yu, and Jen-Chieh Chien

***Abstract*—In this paper, we propose a novel SPSA-based on-line adaptive decoupled control scheme by using PID neural network for a class of nonlinear systems. In addition, the update laws of parameters with adaptive optimal learning rate are proposed based on the Lyapunov stability theorem, this guarantees the stability of closed-loop system. In addition, the affect of the frictional force model and uncertainty are discussed and analyzes. The proposed approach is applied in the translational oscillations with a rotational actuator (TORA) system. In experimental results, the proposed control is realized by DSP to demonstrate the performance and the efficiency.**

***Index Terms*—adaptive control, PID neural network, simultaneous perturbation stochastic approximation, real-time control.**

I. Introduction

RECENTLY, intelligent control systems using fuzzy logic system and neural networks are widely applied for particular systems [2, 11-12, 14, 17]. The neural networks are used to approximate the complicated mathematical function of nonlinear systems when the physical mathematical model is not exactly known. For the training of neural networks, there are many optimization problems which only the measurement of the objective function is available. To develop the neural-network-based controller, the corresponding adaptive laws should be derived by the measurement of objective function. Many approaches were introduced to train the neural networks [5, 9, 11-12, 14-15, 17-18]. However, the usually used methods are gradient descent method and Lyapunov approach. However, it is difficult to obtain the system's gradient information exactly. Therefore, the simultaneous perturbation stochastic approximation (SPSA) is proposed to solve these problems [23, 27-29]. By using SPSA, we can only measure the objective function to solve the optimization problem for providing the adaptive laws of neural networks.

In this paper, we propose a novel SPSA-based on-line adaptive decoupled control scheme by using PID neural network for a class of nonlinear systems. The sliding-mode control (SMC) has been suggested as an approach for the control of systems with nonlinearities, uncertain dynamics and bounded input disturbances [1-2, 7-10, 21, 22, 24]. The SMC-based decoupled architecture is adopted for simplifying the computational complexity. The weights of the PID NN are updated according to the results of SPSA algorithm for the purpose of controlling the system states to stay in sliding surface. By using the SPSA update laws, we can adjust the PID neural network's parameters to achieve the stability of closed-loop system. The proposed approach is applied in the translational oscillations with a rotational actuator (TORA) system. In experimental results, the proposed control is realized by DSP to demonstrate the performance and the efficiency.

This paper is organized as follows. Section II introduces the problem formulations and PID neural networks. The proposed on-line adaptive decoupled control scheme is introduced in Section III. Experimental results of TORA system are shown in Section IV. Finally, the conclusion is given.

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II. Preliminaries

A. Problem Formulation

Consider the following nonlinear coupled system

$$\begin{aligned}
&\dot{x}_{11} = x_{12} && \dot{x}_{21} = x_{22}\\
&\dot{x}_{12} = x_{13} && \dot{x}_{22} = x_{23}\\
&\quad\vdots && \quad\vdots\\
&\dot{x}_{1n} = f_1(\mathbf{X}) + g_1(\mathbf{X})\cdot u + d_1, && \dot{x}_{2n} = f_2(\mathbf{X}) + g_2(\mathbf{X})\cdot u + d_2,\\
&y_1 = x_1, y_2 = x_2
\end{aligned} \tag{1}$$

where $\mathbf{X} = [\mathbf{X}_1^T \mathbf{X}_2^T]^T = [x_{11}\ \dot{x}_{11} \ldots x_{11}^{n-1} x_{21}\ \dot{x}_{21} \ldots x_{21}^{n-1}]^T \in \Re^{2n}$ is system state variable and $y_1, y_2 \in \Re$ are system output. $f_i(\mathbf{X}), g_i(\mathbf{X}) \in \Re$, i=1,2, which satisfy $g_i(\mathbf{X}) \neq 0$, $\forall \mathbf{X} \neq 0$, $t \geq 0$. u is the control input, and $d_1(t)$, $d_2(t)$, are external bounded disturbances, i.e., $|d_1(t)| \leq D_1$, $|d_2(t)| \leq D_2$.

Control objective: In this paper, an adaptive decoupled PID neural network controller is proposed to treat the tracking control problem of system (1), that is the proposed controller generates proper control signal such that the system output y_1 and y_2 follows the continuous bounded desired trajectories y_{r1} and y_{r2}, respectively. Note that the desired trajectories y_{r1}, $y_{r2} \in C^{n-1}$, i.e., the $(n-1)th$ order derivative exist. Thus, we define

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$$\begin{aligned}\mathbf{X}_{r1} &= [x_{r11} \quad \dot{x}_{r11} \quad \cdots \quad x_{r11}^{(n-1)}]^T = [x_{r11} \quad x_{r12} \quad \cdots \quad x_{r1n}]^T \\ \mathbf{X}_{r2} &= [x_{r21} \quad \dot{x}_{r21} \quad \cdots \quad x_{r21}^{(n-1)}]^T = [x_{r21} \quad x_{r22} \quad \cdots \quad x_{r2n}]^T\end{aligned} \quad (2)$$

and the error states are defined as

$$\begin{aligned}\mathbf{e}_1 &= \mathbf{X}_1 - \mathbf{X}_{ri1} \\ \mathbf{e}_2 &= \mathbf{X}_2 - \mathbf{X}_{ri2}\end{aligned}. \quad (3)$$

Therefore, our control objective is transfer into generating proper control signals such that $\mathbf{e}_1$ and $\mathbf{e}_2$ converge to zero when $t\to\infty$.

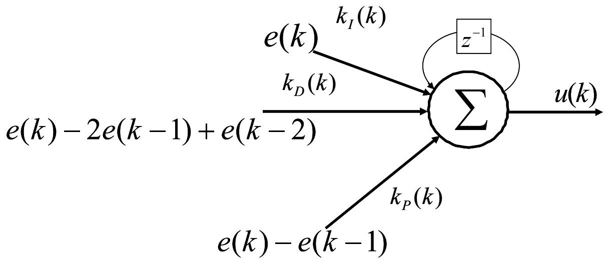

Fig. 1. The structure of PID neural network.

B. PID Neural Network

The proportional integral derivative (PID) controllers are still widely used in process industries even though control theory has been developed significantly since they were first used decades ago. Most of industrial controllers are still implemented based around PID algorithms, particularly at lowest levels, robustness, applicability, and ease of use offered by the PID controller [19]. In addition, neural networks have been applied in many areas including nonlinear control, classification, intelligent control, signal processing, image processing, etc [5, 9-12, 14-15, 17, 19-20, 24, 30-31, 32-33]. Herein, we adopt PID NN controller with adaptive learning rates to produce the control signals. The structure of PID neural network is shown in Fig. 1, the corresponding control input is

$$\begin{aligned}u(k) &= u(k-1) + k_D(k)[e(k) - 2e(k-1) + e(k-2)] \\ &\quad + k_I(k)e(k) + k_P(k)[e(k) - e(k-1)]\end{aligned} \quad (4)$$

where $k_p(k)$, $k_I(k)$, $k_D(k)$ are adaptive adjustable parameters. In our previous literature [16], the gradient-descent method was adopted to derive the adaptive update laws for $k_p(k)$, $k_I(k)$, and $k_D(k)$. However, the system uncertainty, external disturbance, internal noise, and frictional force are unknown. This implies the worse performance of control problem. For solving the problem, we propose an adaptive decoupled PID neural network controller using the SPSA algorithm and SMC technique.

C. Simultaneous Perturbation Stochastic Approximation (SPSA) Algorithm

This section introduces the SPSA algorithm briefly. The detail description can be found in literature [16]. Consider a problem of finding the minimum of objective function $f(W)$. The SPSA algorithm computes the parameter W at next iteration as

$$W(k+1) = W(k) - a(k)g(W(k)) \quad (5)$$

where $g(.)$ is estimated gradient result for objective function $f(.)$, i.e., $\dfrac{\partial f(W)}{\partial W} \approx g(W)$. $a(k)$ is the learning step length which is decreased over iterations with $a(k) = a \big/ (k+A)^{\alpha}$, where a, A, and α are positive configuration coefficients [16]. The SPSA approach estimates the gradient $g(.)$ using following method. Assume that the dimension of parameter W is p. Let $\Delta(k) = [\Delta_1(k)\ \Delta_2(k)\ \ldots\ \Delta_p(k)]$ be a p-dimensional vector whose element is mutually independent zero-mean random variable. Then, the estimation of the gradient at kth iteration can be computed by SPSA algorithm

$$\begin{aligned}g(W(k)) &= \frac{f(W(k) + c(k)\Delta(k)) - f(W(k))}{c(k)} \\ &\quad \cdot [\Delta_1^{-1}(k)\ \Delta_2^{-1}(k)\ \ldots\ \Delta_p^{-1}(k)]^T\end{aligned} \quad (6)$$

where $c(k) = c \big/ (k+1)^{\gamma}$ is gain sequence, where c and γ are nonnegative configuration coefficients. Obviously, all the elements of the parameter W are perturbed simultaneously, and only two measurement of the objective function are needed to estimate the gradient. In addition, $\Delta(k)$ is usually obtained using Bernoulli ± 1 distribution with equal probability for each value.

In general, the gradient information of neural fuzzy system is not easy to obtain due to the asymmetric membership functions and interval valued sets. Herein, we adopt the SPSA algorithm to derive the stable learning rule which guarantees the convergence and stability of the closed-loop systems.

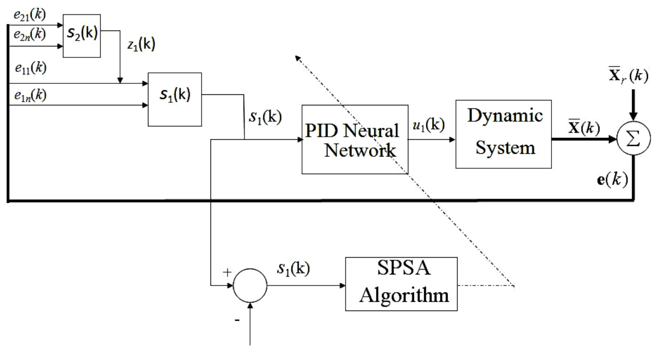

Fig. 3. The proposed decoupled PIDNN control scheme

III. Design of Decoupled Controller Using SPSA Algorithm

A. SMC- based Decoupled Control Design

According equation (3), we define the corresponding sliding mode surface as

$$s_1 = \mathbf{c}_1^T \mathbf{e}_1 - c_{11} z_1 \text{ and } s_2 = \mathbf{c}_2^T \mathbf{e}_2 \quad (7)$$

where $z_1 = z_{U1} sat(\dfrac{s_2}{\Phi_1})$ is called the decoupled factor [22]. sat(.) denotes the saturation function

$$sat(x) = \begin{cases} \operatorname{sgn}(x), & if\ |x| \geq 1 \\ x, & if\ |x| < 1 \end{cases} \quad (8)$$

Herein, $\mathbf{c}_1 = [c_{11}\ c_{12}\ \ldots\ c_{1n-1}]^T$ and $\mathbf{c}_2 = [c_{21}\ c_{22}\ \cdots\ c_{2n-1}\ 1]^T$ are chosen properly such that all eigenvalues of $s_1 = 0$, $s_2 = 0$ are lie in left-half plane. Thus, the tracking error will approach to zero when $s_1 = 0$ and $s_2 = 0$. Figure 3 depicts

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the PID neural network based decoupled adaptive control scheme using SPSA algorithm. The inputs of PID neural network are s_1 and the output is the control signal for nonlinear system.

Our control goal is to minimize the following cost function:

$$E(k) = \frac{1}{2} s_1^2(k) . \tag{9}$$

By the gradient-descent method, the update laws of ith PIDNN's parameters are

$$\begin{bmatrix} k_p(k+1) \\ k_I(k+1) \\ k_D(k+1) \end{bmatrix} = \begin{bmatrix} k_p(k) \\ k_I(k) \\ k_D(k) \end{bmatrix} - \begin{bmatrix} a_P(k) & 0 & 0 \\ 0 & a_I(k) & 0 \\ 0 & 0 & a_D(k) \end{bmatrix} \begin{bmatrix} \frac{\partial E(k)}{\partial k_p} \\ \frac{\partial E(k)}{\partial k_I} \\ \frac{\partial E(k)}{\partial k_D} \end{bmatrix} \tag{10}$$

where $a_P(k)$, $a_I(k)$, $a_D(k)$ are adaptive time varying learning step length. Herein, we use the SPSA algorithm to approximate the gradients of $\frac{\partial E(k)}{\partial k_p}, \frac{\partial E(k)}{\partial k_I}, \frac{\partial E(k)}{\partial k_D}$, thus

$$\begin{bmatrix} \frac{\partial E(k)}{\partial k_p} \\ \frac{\partial E(k)}{\partial k_I} \\ \frac{\partial E(k)}{\partial k_D} \end{bmatrix} \approx \begin{bmatrix} \frac{E_\Delta(k+1) - E(k+1)}{c_\Delta(k)\cdot\Delta_p(k)} \\ \frac{E_\Delta(k+1) - E(k+1)}{c_\Delta(k)\cdot\Delta_I(k)} \\ \frac{E_\Delta(k+1) - E(k+1)}{c_\Delta(k)\cdot\Delta_D(k)} \end{bmatrix} = \begin{bmatrix} \frac{E(\mathbf{W}_\Delta(k)) - E(\mathbf{W}(k))}{c_\Delta(k)\cdot\Delta_p(k)} \\ \frac{E(\mathbf{W}_\Delta(k)) - E(\mathbf{W}(k))}{c_\Delta(k)\cdot\Delta_I(k)} \\ \frac{E(\mathbf{W}_\Delta(k)) - E(\mathbf{W}(k))}{c_\Delta(k)\cdot\Delta_D(k)} \end{bmatrix} \tag{11}$$

where $\mathbf{W}(k) = [k_p(k)\ \ k_I(k)\ \ k_D(k)]^T$, $\mathbf{W}_\Delta(k) = [k_p(k) + c_\Delta(k)\cdot\Delta_p(k) k_I(k)\ + c_\Delta(k)\cdot\Delta_I(k)\ \ k_D(k) + c_\Delta(k)\ \cdot\Delta_D(k)]^T$, $c_\Delta(k) \in \Re$ is perturbation that between 0 and 1. $\Delta_P(k)$, $\Delta_I(k)$, $\Delta_D(k)$ are perturbation ones whose elements are either 1 or -1 in random.

From equations (10) and (11), the update laws of $k_p(k)$, $k_I(k)$, $k_D(k)$ are represented as

$$\begin{aligned} k_P(k+1) = k_P(k) - a_P(k)\cdot s_1(k)\cdot[g_1(\overline{\mathbf{X}}(k))] \\ \cdot\Bigg[\frac{c_\Delta(k)\cdot\Delta_I(k)\cdot s_1(k)}{c_\Delta(k)\cdot\Delta_p(k)} + \frac{c_\Delta(k)\cdot\Delta_D(k)s_1(k)}{c_\Delta(k)\cdot\Delta_p(k)} \\ + \frac{c_\Delta(k)\cdot\Delta_D(k)[-2s_1(k-1)+s_1(k-2)]}{c_\Delta(k)\cdot\Delta_p(k)} \\ + \frac{c_\Delta(k)\cdot\Delta_P(k)[s_1(k)-s_1(k-1)]}{c_\Delta(k)\cdot\Delta_P(k)}\Bigg] \end{aligned} \tag{12}$$

$$\begin{aligned} k_I(k+1) = k_I(k) - a_I(k)\cdot s_1(k)\cdot[g_1(\overline{\mathbf{X}}(k))] \\ \cdot\Bigg[\frac{c_\Delta(k)\cdot\Delta_I(k)\cdot s_1(k)}{c_\Delta(k)\cdot\Delta_I(k)} + \frac{c_\Delta(k)\cdot\Delta_D(k)s_1(k)}{c_\Delta(k)\cdot\Delta_I(k)} \\ + \frac{c_\Delta(k)\cdot\Delta_D(k)[-2s_1(k-1)+s_1(k-2)]}{c_\Delta(k)\cdot\Delta_I(k)} \\ + \frac{c_\Delta(k)\cdot\Delta_P(k)[s_1(k)-s_1(k-1)]}{c_\Delta(k)\cdot\Delta_I(k)}\Bigg] \end{aligned} \tag{13}$$

$$\begin{aligned} k_D(k+1) = k_D(k) - a_D(k)\cdot s_1(k)\cdot[g_1(\overline{\mathbf{X}}(k))] \\ \cdot\Bigg[\frac{c_\Delta(k)\cdot\Delta_I(k)\cdot s_1(k)}{c_\Delta(k)\cdot\Delta_D(k)} + \frac{c_\Delta(k)\cdot\Delta_D(k)s_1(k)}{c_\Delta(k)\cdot\Delta_D(k)} \\ + \frac{c_\Delta(k)\cdot\Delta_D(k)[-2s_1(k-1)+s_1(k-2)]}{c_\Delta(k)\cdot\Delta_D(k)} \\ + \frac{c_\Delta(k)\cdot\Delta_P(k)[s_1(k)-s_1(k-1)]}{c_\Delta(k)\cdot\Delta_D(k)}\Bigg]. \end{aligned} \tag{14}$$

B. Stability analysis

Herein, we develop the convergence theorem for selecting appropriate learning step length $a(k)$. The choice of learning step length is very important for convergence. If a small value is given for the learning step length, the convergence of the closed-loop system is guaranteed. However, the convergent speed may be very slow. On the other hand, if a large value is given, the system may be unstable. Hence, we employ the Lyapunov stability analysis approach to have the condition for convergence and find the optimal learning step length. We have the following theorem for control scheme.

Theorem 1. Let $a_P(k)$, $a_I(k)$, $a_D(k)$ be adaptive learning step length for PID neural network tuning parameters. Consider the nonlinear control problem (shown in Fig. 3), the asymptotic convergence of the closed-loop system is guarantee if the learning step length is chosen satisfying

$$0 < a(k) < \frac{2}{|g(k)|^2}, \text{ for all } k \tag{15}$$

where

$$g(W(k)) = \frac{s_1(W(k) + c(k)\Delta(k)) - s_1(W(k))}{c(k)} \cdot \left[\Delta_1^{-1}(k)\ \Delta_2^{-1}(k)\ \ldots\ \Delta_p^{-1}(k)\right]^T$$

is the gradient estimation using SPSA approach. In addition, the faster convergence can be obtained by using the following optimal time-varying learning step length

$$\begin{aligned} a_P(k) &= \min(1, \frac{1}{3[(s_1(k) - s_1(k-1))g_1(\mathbf{X}(k))]^2}) \\ a_I(k) &= \min(1, \frac{1}{3[s_1(k)g_1(\mathbf{X}(k))]^2}) \\ a_D(k) &= \min(1, \frac{1}{3[(s_1(k) - 2s_1(k-1) + s_1(k-2))g_1(\mathbf{X}(k))]^2}) \end{aligned} \tag{16}$$

Proof: The proof is omitted due to the writing space.

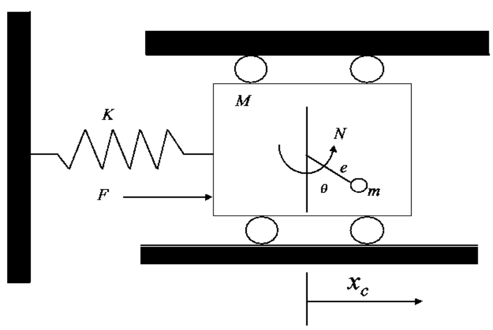

Fig. 4. TORA system.

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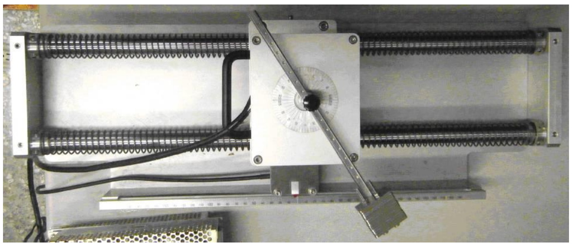

Fig. 5. Experimental equipment of the developed TORA systems at YZU.

IV. Application in Nonlinear TORA System and Experimental Results

In the early 1990s, *Bupp et. al* proposed a benchmark problem for nonlinear control design [3-4, 26]. This benchmark problem consists of the motion control of a cart possessing one translational degree of freedom, which is actuated by an eccentric rotational mass actuator mounted on the cart. The system of cart and rotational actuator is referred to as the so-called TORA system or RTAC (Rotational/Translational Actuator) system. The schematic representation of the TORA system is shown in Fig. 4, which comprises a cart of mass M that is connected to a spring of stiffness K fixed to a wall. The cart is perturbed by a disturbance force F. There is a rotating arm of mass m and length e in the center of the cart. The pendulum is actuated by the control input N. The cart and pendulum move in the horizontal plane, where x_c and $\dot{x}_c$ denote the normalized translational position and velocity of the cart, respectively, and θ and $\dot{\theta}$ denote the angular position and velocity of the rotational actuator [13].

Based on the generalized coordinates $[x_C, \dot{x}_C, \theta, \dot{\theta}]^T$, the motion equations of an ideal TORA system are

$$\begin{aligned}(M+m)\ddot{x}_c + Kx_c &= -me(\ddot{\theta}\cos\theta - \dot{\theta}^2\sin\theta) + F\\ (I+me^2)\ddot{\theta} &= -me\ddot{x}_c\cos\theta + N.\end{aligned} \tag{17}$$

The torque N is generated by the DC motor and is proportional to the current i fed to the motor, i.e., $N=k_T i$, where k_T=18.26 mN/A is the motor constant. By the following normalization and state transformation, we have the following state space representation

$$\dot{x} = f(x) + g(x)u + p_1(x)F_d + p_2(x)u_d \tag{18}$$

where ε is the coupled coefficients of horizontal and

$$f(x)=\begin{bmatrix} x_2 \\ \dfrac{-x_1+\varepsilon x_4{}^2\sin x_3}{1-\varepsilon^2\cos^2 x_3} \\ x_4 \\ \dfrac{\varepsilon\cos x_3\left(x_1-\varepsilon x_4{}^2\sin x_3\right)}{1-\varepsilon^2\cos^2 x_3}\end{bmatrix},\quad g(x)=\begin{bmatrix} 0 \\ \dfrac{-\varepsilon\cos x_3}{1-\varepsilon^2\cos^2 x_3} \\ 0 \\ \dfrac{1}{1-\varepsilon^2\cos^2 x_3}\end{bmatrix},$$

$$p_1(x)=\begin{bmatrix} 0 \\ \dfrac{1}{1-\varepsilon^2\cos^2 x_3} \\ 0 \\ \dfrac{-\varepsilon\cos x_3}{1-\varepsilon^2\cos^2 x_3}\end{bmatrix},\qquad p_2(x)=\begin{bmatrix} 0 \\ \dfrac{-\varepsilon\cos x_3}{1-\varepsilon^2\cos^2 x_3} \\ 0 \\ \dfrac{1}{1-\varepsilon^2\cos^2 x_3}\end{bmatrix}.$$

According system (1), we define $\mathbf{x}=\left[x_{111}, x_{112}, x_{121}, x_{122}\right]^T$ $=\left[x_d, \dot{x}_d, \theta, \dot{\theta}\right]^T$. The experimental setup consists of a DC motor, a motor driver, a personal computer, a D/A control card, an open-type linear scale, and a rotational encoder and is located in the Intelligent Control and Applications Laboratory at Yuan Ze University. The experimental equipment of developed TORA system is shown in Fig. 5.

Case1: Stability Illustration (system having frictional force)

In this simulation, coefficients are chosen as $z_{U11}=0.9$, $\phi_{11}=10$, $c_{111}=10$, $c_{121}=0.5$. The TORA initial condition is $x=[0.07\ 0\ 0\ 0]^T$. PIDNN initial parameters are set to be k_P=0, k_I=0, k_D=0 and the friction force are identified as [13]

$$F_f = 1.33\dot{x}_c + 0.5\operatorname{sgn}(\dot{x}_c),\ N_f = 0.01\dot{\theta} + 0.04\operatorname{sgn}(\dot{\theta}) \tag{19}$$

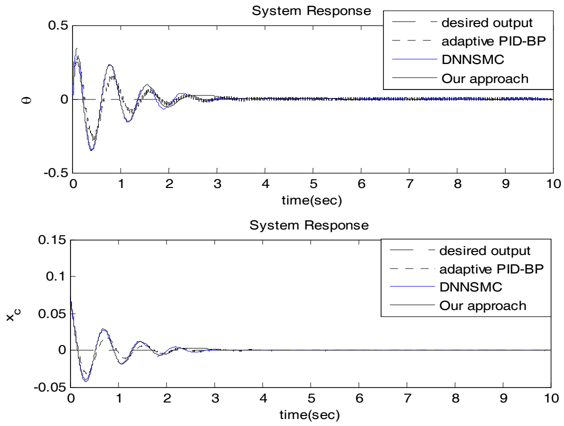

Fig. 6. Comparison results (dotted: PID-BP [16]; dashed: DNN SMC [6]; solid: our approach).

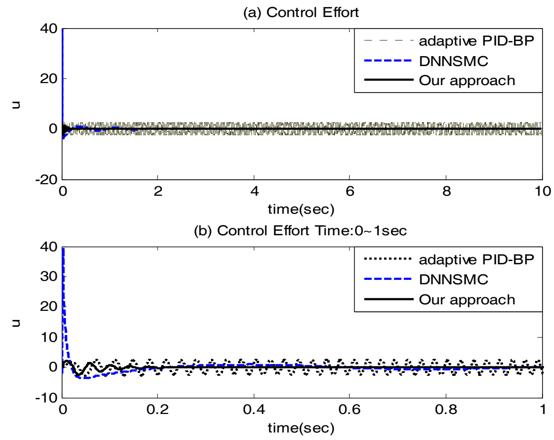

Fig. 7. Comparison results of control effort (dotted: PID-BP [16]; dashed: DNN SMC [6]; solid: our approach).

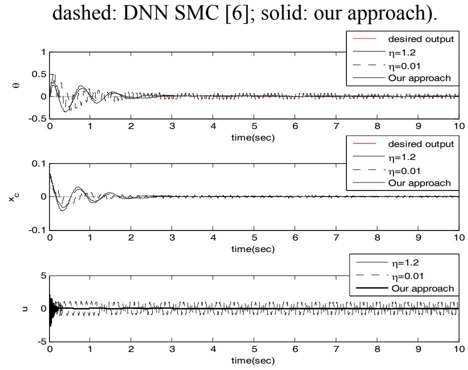

Fig. 8. Comparison results using difference learning step lengths (dashed: fixed value 1.2; dotted: fixed value: 0.01; solid: our approach in equation (16)).

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Figure 6 shows the simulation results when the system having frictional force. We can observe that the proposed approach has the better performance in convergence. The corresponding control effort is shown in Fig. 7. Figure 7(b) shows the control effort between 0~1 sec. It is also found that the proposed approach has more reasonable control effort than other literature [6, 16]. Figure 8 shows the simulation results of our approach using difference fixed learning step length and adaptive step length (16). Also, we find that the proposed adaptive learning step length performs well by using SPSA.

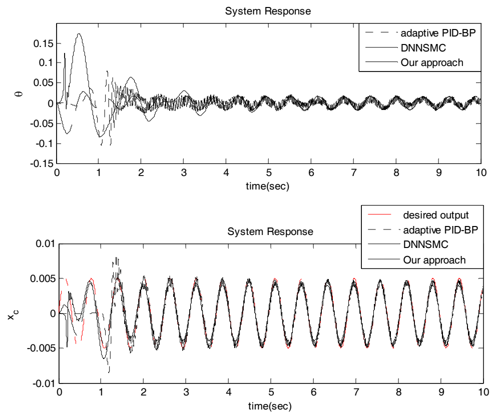

Fig. 9. Comparison results of oscillation control (dotted: PID-BP [16]; dashed: DNN SMC [6]; solid: our approach).

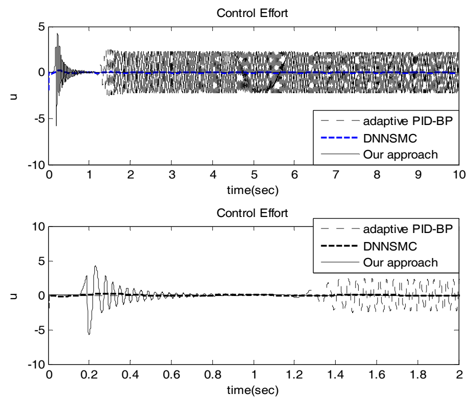

Fig. 10. Comparison results in control effort of oscillation control (dotted: PID-BP [16]; dashed: DNN SMC [6]; solid: our approach).

Case2: Oscillation Control Illustration (system having frictional force)

In addition, we use the following illustrated examples, oscillation control problem, to show that the controller can reduce the influence of uncertainty. These are used to demonstrate the effectiveness and ability of the proposed control scheme. The initial conditions of the following oscillation control are selected as $x_C(0)=0$ [m], $\dot{x}_C(0)=0$ [m/s], $\theta(0)=0$ [deg] and $\dot{\theta}(0)=0$ [deg/s], and the desired trajectory is derived from the oscillation frequency, i.e., $x_{cd}=0.005\sin(10.15t)$. The *Oscillation control* case is considered.

As above, Fig. 9 shows the simulation results when the system having frictional force. We can observe that the proposed approach has the better performance in convergence. The corresponding control effort is shown in Fig. 10, Fig. 10(b) is control effort between 0 to 1 sec. It is also found that the proposed approach has more reasonable control effort than other literature [6, 16]. Figure 11 shows the simulation results of our approach using difference fixed learning step length and adaptive step length (16). Also, we find that the proposed adaptive learning step length performs well by using SPSA.

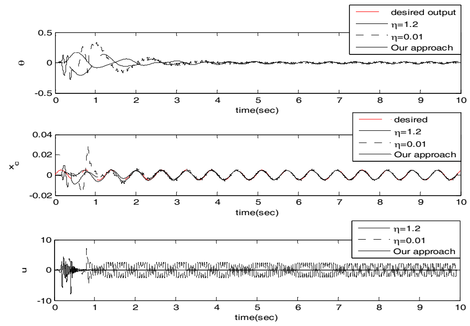

Fig. 11. Comparison results of oscillation control case using difference learning step lengths (dashed: fixed value 1.2; dotted: fixed value: 0.01; solid: our approach in equation (16)).

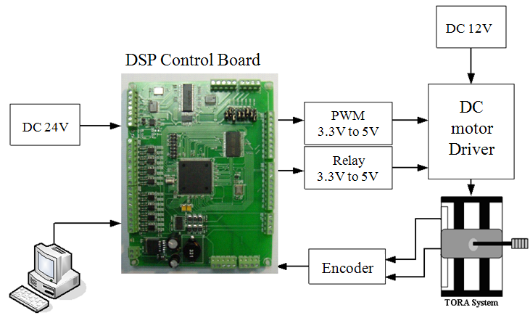

Fig. 12. DSP-based control platform for the TORA system.

Experimental Results of TORA System using DSP-based Control Scheme

The experimental equipment block diagram of the DSP-based control system f or the TORA system are depicted in Fig. 12. Figure 13 shows the experimental result of stability problem. The proposed approach has good performance (converge to zero in small stabilizing time) in experimental equipment. Figure 14 shows the state trajectories of our approach with fixed learning step length and adaptive step length (16). This result illustrates the effectiveness and ability of the adaptive learning step length.

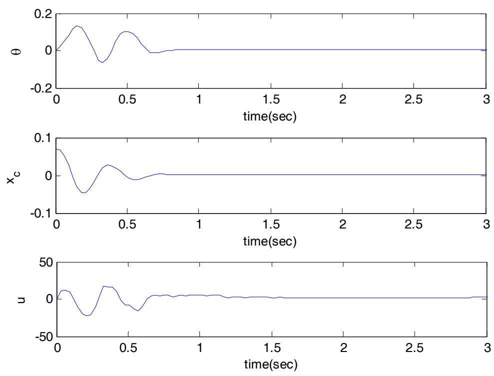

Fig. 13. Experimental result of our approach.

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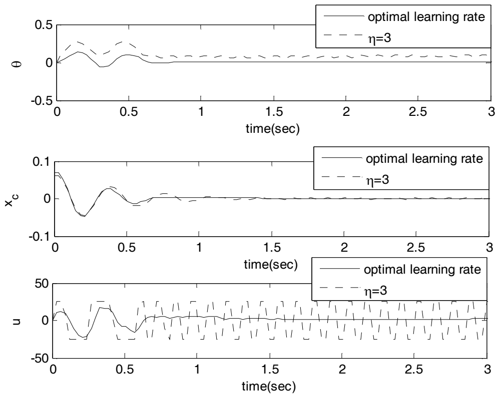

Fig. 14. Comparison results of experimental results by using fixed learning step length and adaptive step length (16).

V. CONCLUSION

In this paper, we have proposed a novel SPSA-based on-line adaptive decoupled control scheme by using PID neural network for a class of nonlinear systems. In addition, the update laws of parameters with adaptive optimal learning rate are proposed based on the Lyapunov stability theorem, this guarantees the stability and performance of closed-loop system. The affect of the frictional force model and uncertainty are discussed and analyzes. The proposed approach is applied in the TORA system. In experimental results, the proposed control has been realized by DSP to demonstrate the performance and the efficiency.

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