Design of Self-Constructing Fuzzy Wavelet Neural Control System

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***Abstract*—In this paper, a self-constructing fuzzy wavelet neural network (SFWNN) is used to approximate an unknown nonlinear term in the system dynamics with the structure and parameter learning abilities concurrently. Further, a self-constructing fuzzy wavelet neural control (SFWNC) system, which is composed of a computation controller and a robust compensator, is proposed. The computation controller using the SFWNN approximator is the main controller and the robust compensator is designed to eliminate the effect of the approximation error. All controller parameters of the SFWNC system are adaptively update based on the Lyapunov stability theory and the projection algorithm to guarantee the closed-loop system stability. Finally, the effectiveness of the proposed SFWNC system is verified by simulation results and the SFWNN approximator has the admirable property of small fuzzy rules size and high learning accuracy.**

Keywords—intelligent control; Lyapunov stability theory; fuzzy neural network; wavelet neural network; self construction.

I. INTRODUCTION

Sliding-mode control (SMC) system is based on the design of a high-speed switching control law that drives the system trajectory onto a sliding surface [1]. Owing to its robustness, the SMC system has been used in many control applications, such as robot manipulators, aircrafts, motor drivers, and power electronic. Recently, some researchers proposed a complementary sliding-mode control (CSMC) system to alleviate the chattering phenomena [2, 3]. With the CSMC approach, the guaranteed tracking precision has been shown to reduce at least by half, as compared with the conventional SMC system [2]. However, the CSMC system is not suitable for real-time applications due to the plant model are unknown or perturbed.

Due to the learning capability of wavelet neural networks (WNNs) is more efficient than that of the sigmoidal function neural networks, there has been considerable interest in exploring the applications of the WNNs to deal with the nonlinearity and uncertainties of control systems [4-6]. Recently, wavelet fuzzy networks (WFNs) are developed based on fuzzy sets [7-11], thus WFN has the merits of the low-level learning for neural network and the high-level human knowledge for fuzzy theory. However, the learning laws of WFN only consider parameter learning without structure adjustment. To overcome this problem, several self-constructing fuzzy wavelet neural networks (SFWNNs) are proposed whereby structure and parameters could be on-line learned simultaneously [12-14]. Thus, SFWNN is suitable for fast on-line learning control applications.

The contribution of this paper is to design a self-constructing fuzzy wavelet neural control (SFWNC) scheme by inheriting the robust property of CSMC scheme. This paper is organized into five sections. Following the introduction, Section 2 gives a description of SFWNN approximator for generating the network structure. In Section 3, an SFWNC system is proposed, where the SFWNN approximator is used to approximate an unknown nonlinear term in the system dynamics with the structure and parameter learning abilities concurrently. The adaptation laws in the SFWNC system are derived in the sense of Lyapunov stability theorem and projection algorithm, so that the system tracking stability can be guaranteed. In Section 4, the SFWNC system is applied to control an inverted pendulum. The simulation results show that the SFWNC system can achieve favorable tracking performance even under parameter variations and unknown disturbances in the plant. Finally, some conclusions are drawn in Section 5.

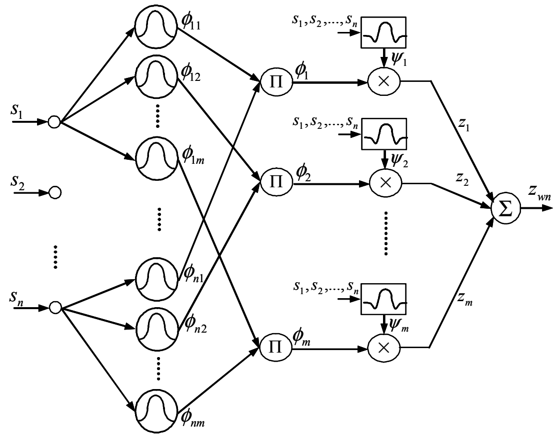

Fig. 1. Network structure of SFWNN approximator.

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II. Description of SFWNN Approximator

The SFWNN is proposed whereby structure and parameters could be on-line learned, simultaneously, where the network structure of SFWNN approximator is shown in Fig. 1. Fuzzy rule is described as follows

Rule i: IF s_1 is A_{1i} and … and s_n is A_{ni},

THEN z_{wn} is $z_i(1, s_1, ..., s_n)$, for $i = 1,2,...,m$ (1)

where m is the total number of existing fuzzy rules, $s_1, s_2, ..., s_n$ are the input variables, and z_{wn} is the output variable. The Gaussian fuzzy sets are in the antecedent part and the linear combination of input variables are in the consequence part. A_{ji} represents a fuzzy set that is described as

$$\phi_{ji} = \exp\left(-\frac{(s_j - c_{ji})^2}{(\sigma_{ji})^2}\right) \tag{2}$$

where σ_{ji} and c_{ji} are the deviation and mean of the Gaussian function in the j-th term, respectively. Thus, given an input dataset $(s_1, s_2 ..., s_n)$, the firing weight ϕ_i of Rule i is calculated by

$$\phi_i(\boldsymbol{\sigma}_i, \mathbf{c}_i) = \prod_{j=1}^{n} \phi_{ji} \tag{3}$$

where $\boldsymbol{\sigma}_i = [\sigma_{1i}, \sigma_{2i}, \ldots, \sigma_{ni}]^T$ and $\mathbf{c}_i = [c_{1i}, c_{2i}, \ldots, c_{ni}]^T$. Meanwhile, the "Mexican hat" wavelet function is designed as $\psi_i = \prod_{j=1}^{n}(1 - \omega_{ji}^2 s_j^2)$ and the consequent part is given as

$$z_i = \alpha_{i0} + \sum_{j=1}^{n} \alpha_{ij} s_j = \boldsymbol{\alpha}_i^T \mathbf{s} \tag{4}$$

where $\mathbf{s} = [1, s_1, s_2 ..., s_n]^T$ and $\boldsymbol{\alpha}_i = [\alpha_{i0}, \alpha_{i1}, ..., \alpha_{in}]^T$ for a first-order TSK type fuzzy rule. Thus, the SFWNN output can be obtained as

$$z_{wn} = \sum_{i=1}^{m} z_i \psi_i \phi_i(\boldsymbol{\sigma}_i, \mathbf{c}_i) = \boldsymbol{\alpha}^T \boldsymbol{\Theta}(\boldsymbol{\sigma}, \mathbf{c}) \tag{5}$$

where $\boldsymbol{\alpha} = [\boldsymbol{\alpha}_1^T, \boldsymbol{\alpha}_2^T, \ldots, \boldsymbol{\alpha}_m^T]^T$, $\boldsymbol{\Theta} = [\psi_1\phi_1\mathbf{s}^T, \psi_2\phi_2\mathbf{s}^T, \ldots, \psi_m\phi_m\mathbf{s}^T]^T$, $\boldsymbol{\sigma} = [\boldsymbol{\sigma}_1^T, \boldsymbol{\sigma}_2^T, \ldots, \boldsymbol{\sigma}_m^T]^T$ and $\mathbf{c} = [\mathbf{c}_1^T, \mathbf{c}_2^T, \ldots, \mathbf{c}_m^T]^T$.

A structuring learning mechanism for generation and removal of fuzzy rules is proposed. For the first input data $(s_1, s_2 ..., s_n)$, an initial fuzzy rule is generated with the parameters are given as

$$\boldsymbol{\alpha}_1 = \mathbf{0},\ \boldsymbol{\sigma}_1 = \overline{\boldsymbol{\sigma}},\ \mathbf{c}_1 = [s_1, s_2, ..., s_n]^T \tag{6}$$

where $\overline{\boldsymbol{\sigma}}$ is a parameter vector specified by designers. Define the distance measure between the new input data $(s_1, s_2 ..., s_n)$ and the existing membership function centers as

$$d_i = \left\| [s_1, s_2, ..., s_n]^T - \mathbf{c}_i \right\| \tag{7}$$

Find the nearest distance measure defines as

$$d_{\min} = \min_{1 \le i \le m} d_i \tag{8}$$

If $d_{\min} > d_G$ is satisfied, where d_G a pre-given threshold, it means that there does not exist any fuzzy rule representing the new input data. A new fuzzy rule should be created to accommodate input partitioning with the initial adjustable parameters assigned as follows

$$\boldsymbol{\alpha}_{m+1} = \mathbf{0},\ \boldsymbol{\sigma}_{m+1} = \overline{\boldsymbol{\sigma}},\ \mathbf{c}_{m+1} = [s_1, s_2, ..., s_n]^T \tag{9}$$

Further, to reduce the number of fuzzy rules, a significance index of the i-th fuzzy rule is applied as [15]

$$I_j = \begin{cases} I_j^{pre} \exp(-\tau_1), & if\ d_j \ge d_{th} \\ I_j^{pre}\left(2 - \exp\left(-\tau_2\left(1 - I_j^{pre}\right)\right)\right), & if\ d_j < d_{th} \end{cases} \tag{10}$$

where I_j^{pre} is the significance index in the previous time and τ_1 and τ_2 are the designed constant. If $I_j \le I_R$ is satisfied, where I_R a pre-given threshold, then the j-th fuzzy rule is insignificant and will be removed from SFWNN approximator.

According to the powerful approximation ability, there exists an ideal SFWNN approximator z_{wn}^* to on-line approximate the nonlinear term z as

$$z = z_{wn}^* + \Delta = \boldsymbol{\alpha}^{*T} \boldsymbol{\Theta}(\boldsymbol{\sigma}^*, \mathbf{c}^*) + \Delta = \boldsymbol{\alpha}^{*T} \boldsymbol{\Theta}^* + \Delta \tag{11}$$

where Δ denotes the approximation error, and $\boldsymbol{\alpha}^*$, $\boldsymbol{\Theta}^*$, $\boldsymbol{\sigma}^*$ and $\mathbf{c}^*$ are the optimal parameter vectors of $\boldsymbol{\alpha}$, $\boldsymbol{\Theta}$, $\boldsymbol{\sigma}$ and $\mathbf{c}$, respectively. The estimated SFWNN approximator $\hat{z}_{wn}$ in the control law is assumed to take the following form

$$\hat{z}_{wn} = \hat{\boldsymbol{\alpha}}^T \boldsymbol{\Theta}(\hat{\boldsymbol{\sigma}}, \hat{\mathbf{c}}) = \hat{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\Theta}} \tag{12}$$

where $\hat{\boldsymbol{\alpha}}$, $\hat{\boldsymbol{\Theta}}$, $\hat{\boldsymbol{\sigma}}$ and $\hat{\mathbf{c}}$ are the estimated parameter vectors of $\boldsymbol{\alpha}$, $\boldsymbol{\Theta}$, $\boldsymbol{\sigma}$ and $\mathbf{c}$, respectively. Then, the estimation error is obtained as

$$\tilde{z} = \boldsymbol{\alpha}^{*T}\boldsymbol{\Theta}^* - \hat{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\Theta}} + \Delta$$
$$= \tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\Theta}} + \hat{\boldsymbol{\alpha}}^T\tilde{\boldsymbol{\Theta}} + \tilde{\boldsymbol{\alpha}}^T\tilde{\boldsymbol{\Theta}} + \Delta \quad (13)$$

where $\tilde{\boldsymbol{\alpha}} = \boldsymbol{\alpha}^* - \hat{\boldsymbol{\alpha}}$ and $\tilde{\boldsymbol{\Theta}} = \boldsymbol{\Theta}^* - \hat{\boldsymbol{\Theta}}$. Using the expansion of $\tilde{\boldsymbol{\Theta}}$ in a Taylor series [16, 17], (13) can obtain

$$\tilde{z} = \tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\Theta}} + \hat{\boldsymbol{\alpha}}^T\left(\mathbf{A}^T\tilde{\boldsymbol{\sigma}} + \mathbf{B}^T\tilde{\mathbf{c}} + \mathbf{h}\right) + \tilde{\boldsymbol{\alpha}}^T\tilde{\boldsymbol{\Theta}} + \Delta$$
$$= \tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\Theta}} + \tilde{\boldsymbol{\sigma}}^T\mathbf{A}\hat{\boldsymbol{\alpha}} + \tilde{\mathbf{c}}^T\mathbf{B}\hat{\boldsymbol{\alpha}} + \varepsilon \quad (14)$$

where $\tilde{\mathbf{c}} = \mathbf{c}^* - \hat{\mathbf{c}}$, $\tilde{\boldsymbol{\sigma}} = \boldsymbol{\sigma}^* - \hat{\boldsymbol{\sigma}}$, $\mathbf{h}$ is a vector of high order terms, $\mathbf{A} = \left[\frac{\partial\Theta_1}{\partial\boldsymbol{\sigma}} \cdots \frac{\partial\Theta_{m(t)}}{\partial\boldsymbol{\sigma}}\right]\big|_{\boldsymbol{\sigma}=\hat{\boldsymbol{\sigma}}}$, $\mathbf{B} = \left[\frac{\partial\Theta_1}{\partial\mathbf{c}} \cdots \frac{\partial\Theta_{m(t)}}{\partial\mathbf{c}}\right]\big|_{\mathbf{c}=\hat{\mathbf{c}}}$ and $\varepsilon = \hat{\boldsymbol{\alpha}}^T\mathbf{h} + \tilde{\boldsymbol{\alpha}}^T\tilde{\boldsymbol{\Theta}} + \Delta$ denotes the lump of approximation error which is assumed to be bounded by $|\varepsilon| \le E$.

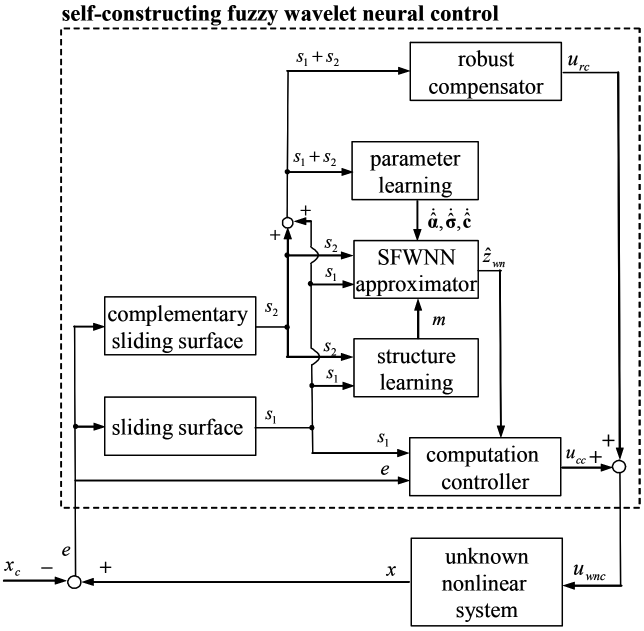

Fig. 2. The block diagram of the SFWNC system.

III. Design of SFWNC System

A second-order nonlinear plant is expressed in the following form as

$$\ddot{x} = f + gu \quad (15)$$

where x is the system state, f and $g > 0$ are the unknown system dynamics, and u is the control input. The control objective in tracking systems is to find a control law to drive the system state x to the state command x_c. To design the control law, the error dynamic can be obtained as

$$\ddot{e} = z + u \quad (16)$$

where $e = x - x_c$ is the tracking error, z is the unknown nonlinear term that defined as $z = -\ddot{x}_c + \left(1 - \frac{1}{g}\right)\ddot{x} + \frac{f}{g}$. A sliding surface is designed as [2, 3]

$$s_1 = \dot{e} + 2\lambda e + \lambda^2\int_0^t e(\tau)d\tau \quad (17)$$

where λ is a positive constant and a complementary sliding surface is designed as [2, 3]

$$s_2 = \dot{e} - \lambda^2\int_0^t e(\tau)d\tau \quad (18)$$

Meanwhile, a significant result can be obtained as [2, 3]

$$\dot{s}_2 = \dot{s}_1 - \lambda(s_1 + s_2) \quad (19)$$

The output of the SFWNC system as shown in Fig. 2 is designed as

$$u_{wnc} = u_{cc} + u_{rc} = -\hat{z}_{wn} - \lambda(2\dot{e} + \lambda e + s_1) + u_{rc} \quad (20)$$

where the computation controller u_{cc} serves as the main control and the robust compensator u_{rc} is designed to eliminate the effect of the approximation error upon system stability. We can obtain that

$$\dot{s}_1 = z + u + 2\lambda\dot{e} + \lambda^2 e$$
$$= z - \hat{z}_{wn} - \lambda s_1 + u_{rc}$$
$$= \tilde{z} - \lambda s_1 + u_{rc} \quad (21)$$

where $\tilde{z} = z - \hat{z}_{wn}$. Imposing (14) into (21) yields

$$\dot{s}_1 = \tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\Theta}} + \tilde{\boldsymbol{\sigma}}^T\mathbf{A}\hat{\boldsymbol{\alpha}} + \tilde{\mathbf{c}}^T\mathbf{B}\hat{\boldsymbol{\alpha}} + \varepsilon - \lambda s_1 + u_{rc} \quad (22)$$

To eliminate the effect of the approximation error ε, this paper designs the robust compensator u_{rc} as [18, 19]

$$u_{rc} = -\frac{E}{\rho + (1-\rho)e^{-|s_1+s_2|}}\operatorname{sgn}(s_1 + s_2) \quad (23)$$

where $\operatorname{sgn}(\cdot)$ is the sign function and ρ is a strictly positive constant that is less than one. Substituting (23) into (22) yields

$$\dot{s}_1 = \tilde{\boldsymbol{\alpha}}^T\hat{\boldsymbol{\Theta}} + \tilde{\boldsymbol{\sigma}}^T\mathbf{A}\hat{\boldsymbol{\alpha}} + \tilde{\mathbf{c}}^T\mathbf{B}\hat{\boldsymbol{\alpha}} + \varepsilon - \lambda s_1$$
$$- \frac{E}{\rho + (1-\rho)e^{-|s_1+s_2|}}\operatorname{sgn}(s_1 + s_2) \quad (24)$$

Theorem 1: Considering a second-order nonlinear system represented in (15), the SFWNC system is designed as (20). The SFWNN approximator are designed $\hat{z}_{wn} = \hat{\boldsymbol{\alpha}}^T \boldsymbol{\Theta}(\hat{\boldsymbol{\sigma}}, \hat{\mathbf{c}})$ with the parameter adaptive laws as follows

$$\dot{\hat{\boldsymbol{\alpha}}} = \eta_\alpha (s_1 + s_2) \hat{\boldsymbol{\Theta}} \ ,$$
$$\text{if } (\|\hat{\boldsymbol{\alpha}}\| < b_\alpha) \text{ or } (\|\hat{\boldsymbol{\alpha}}\| = b_\alpha \text{ and } (s_1 + s_2) \hat{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\Theta}} \le 0) \qquad (25a)$$

$$\dot{\hat{\boldsymbol{\alpha}}} = \eta_\alpha (s_1 + s_2) \hat{\boldsymbol{\Theta}} - \eta_\alpha (s_1 + s_2) \frac{\hat{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\Theta}}}{\|\hat{\boldsymbol{\alpha}}\|^2} \hat{\boldsymbol{\alpha}} \ ,$$
$$\text{if} (\|\hat{\boldsymbol{\alpha}}\| = b_\alpha \text{ and } (s_1 + s_2) \hat{\boldsymbol{\alpha}}^T \hat{\boldsymbol{\Theta}} > 0) \qquad (25b)$$

$$\dot{\hat{\boldsymbol{\sigma}}} = \eta_\sigma (s_1 + s_2) \mathbf{A} \hat{\boldsymbol{\alpha}} \ ,$$
$$\text{if } (\|\hat{\boldsymbol{\sigma}}\| < b_\sigma) \text{ or } (\|\hat{\boldsymbol{\sigma}}\| = b_\sigma \text{ and } (s_1 + s_2) \hat{\boldsymbol{\sigma}}^T \mathbf{A} \hat{\boldsymbol{\alpha}} \le 0) \qquad (26a)$$

$$\dot{\hat{\boldsymbol{\sigma}}} = \eta_\sigma (s_1 + s_2) \mathbf{A} \hat{\boldsymbol{\alpha}} - \eta_\sigma (s_1 + s_2) \frac{\hat{\boldsymbol{\sigma}}^T \mathbf{A} \hat{\boldsymbol{\alpha}}}{\|\hat{\boldsymbol{\sigma}}\|^2} \hat{\boldsymbol{\sigma}} \ ,$$
$$\text{if } (\|\hat{\boldsymbol{\sigma}}\| = b_\sigma \text{ and } (s_1 + s_2) \hat{\boldsymbol{\sigma}}^T \mathbf{A} \hat{\boldsymbol{\alpha}} > 0) \qquad (26b)$$

$$\dot{\hat{\mathbf{c}}} = \eta_c (s_1 + s_2) \mathbf{B} \hat{\boldsymbol{\alpha}} \ ,$$
$$\text{if } (\|\hat{\boldsymbol{\sigma}}\| < b_c) \text{ or } (\|\hat{\mathbf{c}}\| = b_c \text{ and } (s_1 + s_2) \hat{\mathbf{c}}^T \mathbf{B} \hat{\boldsymbol{\alpha}} \le 0) \qquad (27a)$$

$$\dot{\hat{\mathbf{c}}} = \eta_c (s_1 + s_2) \mathbf{B} \hat{\boldsymbol{\alpha}} - \eta_c (s_1 + s_2) \frac{\hat{\mathbf{c}}^T \mathbf{B} \hat{\boldsymbol{\alpha}}}{\|\hat{\mathbf{c}}\|^2} \hat{\mathbf{c}} \ ,$$
$$\text{if } (\|\hat{\mathbf{c}}\| = b_c \text{ and } (s_1 + s_2) \hat{\mathbf{c}}^T \mathbf{B} \hat{\boldsymbol{\alpha}} > 0) \qquad (27b)$$

where η_α, η_c, and η_σ are positive learning rates, $\| \ \|$ denotes the Euclidean norm, b_α, b_σ and b_c are given positive parameter bounds and the robust compensator is designed as (23), then the stability of the SFWNC system can be assured. This means that $s_1 \to 0$ and $s_2 \to 0$ as $t \to \infty$ [2, 3]. As a result, the stable control behavior of the SFWNC system can be ensured.

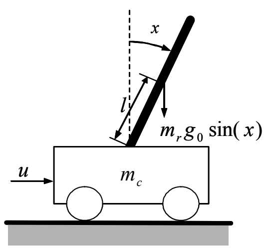

Fig. 3. Inverted pendulum stabilizing problem.

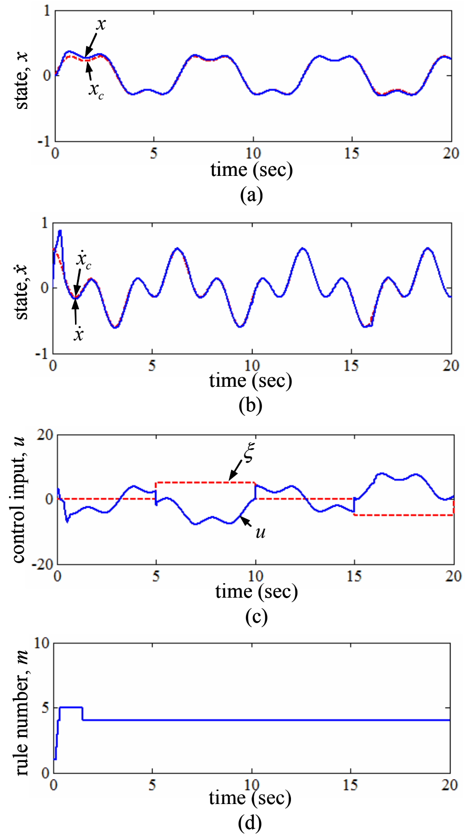

Fig. 4. The simulation results for nominal case.

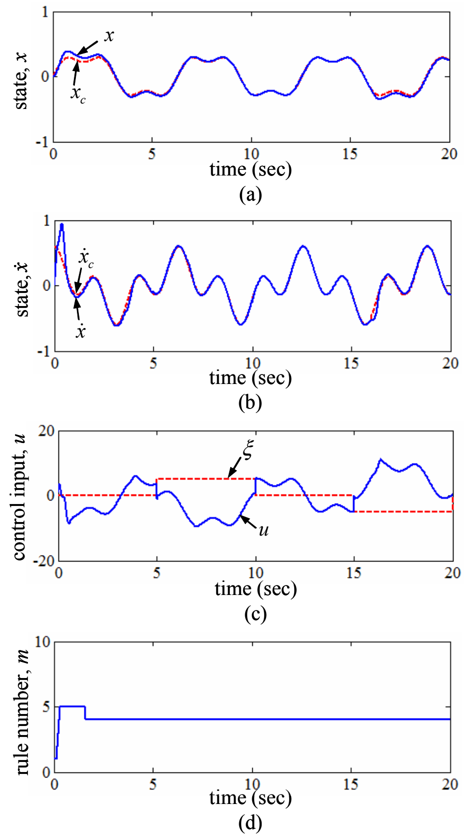

Fig. 5. The simulation results for payload case.

IV. SIMULATION RESULTS

As shown in Fig.3, the dynamic equation of the inverted pendulum is given as

$$\ddot{x} = f + gu + \xi \tag{28}$$

where x is the angle of the pendulum, , $f = \dfrac{m_r l\dot{x}\sin(x)\cos(x) - (m_c + m_r)g_0\sin(x)}{m_r l\cos^2(x) - \frac{4}{3}l(m_c + m_r)}$ and $g = \dfrac{-\cos(x)}{m_r l\cos^2(x) - \frac{4}{3}l(m_c + m_r)}$ are the system dynamics, u is the control input, ξ is the external disturbance $-5 \le \xi \le 5$, $m_c = 1$ is the mass of cart, $m_r = 0.1$ is the mass of rod, $g_0 = 9.81$ is the acceleration due to gravity, and $l = 0.5$ is the half length of rod. Two tested case are applied here. One is the nominal case with $m_r = 0.1$ and the other is the payload case with $m_r = 0.5$.

The parameters of the SFWNC system are selected as $\lambda = 0.5$, $\rho = 0.5$, $\eta_\alpha = 30$, $\eta_\sigma = \eta_c = \eta_E = 2$, $\overline{\boldsymbol{\sigma}} = [0.08, 0.08]^T$, $d_G = 0.15$, $\tau_1 = 0.01$, $\tau_2 = 0.01$, $d_{th} = 0.25$, $I_R = 0.01$ and $E = 0.1$. All of the parameters are determined by trial and error in order to guarantee the desired control performance. The simulation results of the SFWNC system with first-order TSK type SFWNN approximator are shown in Figs. 4 and 5 for nominal case and payload case, respectively. The simulation results verify that favorable performance with fast convergence speed of the tracking error and the dynamic structural adaptation can be achieved. It should be highlighted that the structure learning mechanism of fuzzy rules not only helps automate fuzzy rule generation but also locates good initial rule positions for parameter learning to improve the performance of control.

V. CONCLUSIONS

In this paper, a SFWNN approximator, in which the number of fuzzy rules can effectively generate and prune by the structure learning, is designed to on-line approximate the unknown nonlinear term of the system dynamics. Furthermore, this paper proposes a SFWNC system which is composed of a computation controller and a robust compensator. The system stability of the closed-loop control system can be guaranteed based on the Lyapunov stability theory and the projection algorithm. Finally, the simulation results are provided to demonstrate the robust control performance of the proposed SFWNC scheme due to the SFWNN approximator has the admirable property of small fuzzy rules size and high learning accuracy.

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