Research Article

Self-Organizing Adaptive Wavelet Backstepping Control Research for AC Servo System

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A novel self-organizing adaptive wavelet cerebellar model articulation controller backstepping (SOWCB) control is proposed, aiming at some nonlinear and uncertain factors that caused difficulties in controlling the AC servo system. This controller consists of self-organizing wavelet cerebellar model articulation controller (CMAC) and robust compensator. It absorbs fast learning and precise approaching advantage of self-organizing wavelet CMAC to mimic a backstepping controller, and then robust compensator is added to inhibit influence of the uncertainties on system performance effectively and realize high accuracy position tracking for AC servo system. Moreover, the stability of the control system can be guaranteed by using Lyapunov method. The results of the simulation and the prototype test prove that the proposed approach can improve the steady state performance and control accuracy and possess a strong robustness to both parameter perturbation and load disturbance.

1. Introduction

With the advancement of technology, AC servo systems have become more and more widely utilized. For a servo driving system, the control system is required to have both a strong steady-state and dynamic performance, and it is necessary to build a precise dynamic model of the system for conducting the analysis, simulation, and control of an AC servo system. As a controlled object, the dynamic mathematical model of an AC motor is a complex system, which is characterized by a heavy varying-load, slow time variation, nonlinearity, and uncertain disturbance. Thus, the practical intelligent control strategy has become a focus in the field of servo system control.

Zhou and Zhu [1, 2] use nonlinear backstepping control method that can effectively realize the nonlinear decoupling of AC servo system and ensure the accuracy of the motor servo control at the same time; however, the algorithm requires accurate mathematical model of controlled object that is known; if the controlled object has uncertain amount of interference, the algorithm will not be able to achieve good control effect.

Su and He [3, 4] for uncertain nonlinear system using backstepping control and learning control method of combining designed several adaptive learning controllers; the literature [5–7] uses wavelet neural network approach in the use of complex nonlinear term backstepping process; the control structure has been simplified and improved learning ability.

Cerebellar model articulation controller (CMAC) is modeled on the principle of the cerebellum control body movement established [8, 9]. Peng and Lin [10, 11] use CMAC to replace the traditional neural network approximation to complex nonlinear system. The literature [12] studies a Gaussian basis function neural network, making its generalization ability enhanced. Lee et al. [13] propose a self-organizing genetic neural network algorithm; however the structure design method is too complicated and lacks online learning ability.

Based on the above analysis, this paper uses self-organizing adaptive wavelet cerebellar model articulation controller (SOWC) to online approximation of backstepping controller, using robust control to eliminate system uncertainties and approximation error; finally, simulation

FIGURE 1: The structure diagram of AC servo system.

experiments of AC servo system and the prototype test can prove the effectiveness of the proposed method.

2. Modeling AC Servo System

The structure diagram of an AC servo system is presented in Figure 1, where the magnetic powder brake is the purpose of the change of load simulation system. Because this paper's main consideration is the system load changes caused by the nonlinear of the motor itself is correct, the system load changes brought nonlinear phase comparison that is very small, so the derivation of the model made the following assumptions:

- (1) No saturation effect.
- (2) Induction electromotive force that is sine wave shape; motor air-gap magnetic field distribution.
- (3) Excluding the hysteresis and eddy current loss.
- (4) No rotor excitation winding.

Based on the above assumptions, available under d - q axis two-phase static coordinate system mathematical model is the following:

$$\begin{aligned} \dot{i}_d &= -\frac{R}{L_d} i_d + \frac{L_q}{L_d} p i_q \omega_r + \frac{u_d}{L_d}, \\ \dot{i}_q &= -\frac{R}{L_q} i_q + \frac{L_d}{L_q} p i_d \omega_r - \frac{\psi_f}{L_q} p \omega_r + \frac{u_q}{L_q}, \\ \dot{\omega}_r &= \frac{1}{J} (T_e - T_L - B \omega_r), \end{aligned} \quad (1)$$

where u_d and u_q are d - q axis stator voltage component; i_d and i_q are d - q axis stator current component; L_d , L_q are d - q axis stator inductor component; ψ_f is flux linkage; R is stator resistance; P is pole-pairs; T_L is the load disturbance torque; T_e is electromagnetic torque; J is the total inertia moment converted to the rotor; B is the viscous friction coefficient; ω_r is the rotor velocity of motor; i is the reduction ratio.

Use the method of vector control technology of $i_d = 0$ to achieve linear resolve decoupling control. Mechanical equations can be derived by (1):

$$J \dot{\omega}_b + B \omega_b + T_L = T_e, \quad (2)$$

where ω_b is the angular velocity of motor, $\omega_r = p \omega_b$; the equation of electromagnetic torque is shown as

$$T_e = \frac{3}{2} p \psi_f i_q = K_t i_q, \quad (3)$$

where K_t is torque constant.

Due to the current in the motor time constant being far smaller than the mechanical time constant, the current loop speed is faster than the response speed of the speed loop and position loop, so the current loop approximation can be simplified as a proportion function.

Let variable $x_1 = \theta$, $x_2 = \omega_r = \dot{\theta}$, put (3) into (2), and the state space equation of the speed control system can be rewritten as

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= -\frac{B}{J} x_2(t) + \frac{K_t}{J} i_q(t) + \left(-\frac{1}{J} T_L\right). \end{aligned} \quad (4)$$

Equation (4) can be rewritten as

$$\dot{x}_2 = f(x) x_2(t) + g(x) i_q(t) + d(t), \quad (5)$$

where $f(x) = -B/J$; $g(x) = K_t/J$; $d(t) = -T_L/J$; and $|d(t)| \leq C$, where C is a constant.

3. Self-Organizing Wavelet CMAC Neural Networks

Self-organizing wavelet CMAC network structure diagram is as shown in Figure 2.

The network consists of input space, store space, accepted domain space, weights of storage space, and output space [14]. The output expression is

$$O = u_{\text{owc}}(\mathbf{I}, \mathbf{w}, \mathbf{a}, \mathbf{b}) = \sum_{k=1}^{n_b} \omega_k r_k(\mathbf{I}, \mathbf{a}_k, \mathbf{b}_k), \quad (6)$$

where n_b is layer node; $k = 1, 2, \dots, n_b$; ω_k is the output of weight memory at the k node. r_k is accepted space at the k node; each accepted space layer has different wavelet functions; the r_k can be shown as

$$\begin{aligned} r_k(\mathbf{I}, \mathbf{a}_k, \mathbf{b}_k) &= \prod_{i=1}^{n_a} \mu_{ik} F_{ik} \\ &= -\prod_{i=1}^{n_a} \left(\frac{I_i - a_{ik}}{b_{ik}} \right) \exp \left(\frac{-((I_i - a_{ik})/b_{ik})^2}{2} \right), \end{aligned} \quad (7)$$

where a_{ik} is wavelet translated parameter and b_{ik} is wavelet scaling parameter.

FIGURE 2: The structure of self-organizing wavelet CMAC neural networks.

For the convenience of deriving, the parameter of CMAC can be defined as

$$\begin{aligned}
 \mathbf{I} &= [I_1, \dots, I_{n_a}]^T \in \mathcal{R}^{n_a}; \\
 \mathbf{r} &= [r_1, \dots, r_{n_b}]^T \in \mathcal{R}^{n_b}; \\
 \boldsymbol{\omega} &= [\omega_1, \dots, \omega_{n_b}]^T \in \mathcal{R}^{n_b}; \\
 \mathbf{a}_k &= [a_{1k}, \dots, a_{n_a k}]^T \in \mathcal{R}^{n_a}; \\
 \mathbf{a} &= [\mathbf{a}_1^T, \dots, \mathbf{a}_{n_b}^T]^T \in \mathcal{R}^{n_a n_b}; \\
 \mathbf{b}_k &= [b_{1k}, \dots, b_{n_a k}]^T \in \mathcal{R}^{n_a}; \\
 \mathbf{b} &= [\mathbf{b}_1^T, \dots, \mathbf{b}_{n_b}^T]^T \in \mathcal{R}^{n_a n_b}.
 \end{aligned} \tag{8}$$

3.1. Layer Node Increase. According to the size of the input to increase or decrease the number of nodes, if a new input is valued within the range of this family, the self-organizing cerebellar neural network will no longer produce new node; it will just change the weight [15].

Defined in the association storage space,

$$m_k = r_k, \quad k = 1, 2, \dots, n_b(t), \tag{9}$$

where m_k is measuring degrees of network at k nodes. With the following theory to determine the number of nodes increases, it can be expressed as

$$m_{\max} = \max_{1 \leq k \leq n_b} m_k. \tag{10}$$

Set $m_{\text{th}} \in (0, 1)$ as a predetermined minimum; if it is satisfied by $m_{\max} \leq m_k$, then a new node can be generated by

$$n_b(t+1) = n_b(t) + 1. \tag{11}$$

Translated and scaling parameter in the memory space and weight of the new generation are set to

$$\begin{aligned}
 a_i^{\text{new}} &= I_i; \\
 b_i^{\text{new}} &= b_i; \\
 \omega^{\text{new}} &= 0,
 \end{aligned} \tag{12}$$

where I_i is new input data and b_i is a preset constant.

3.2. Layer Node Decrease. Consider the exponential function at k node is

$$\beta_k(t+1) = \begin{cases} \beta_k(t) \exp(-\tau), & \text{if } m_k(t) < n \\ \beta_k(t), & \text{if } m_k(t) > n, \end{cases} \tag{13}$$

where n is to reduce the threshold; τ is speed constant; $\beta_k(t)$ is the initial value of 1 at the first index k layer, where $k = 1, \dots, n_b(t)$; if β_k is less than a given threshold β_{th} in advance, the first k node should be deleted. This means that, for an output data, if a node for the contribution of output is less than a set value, then this node should be deleted.

4. Self-Organizing Wavelet Adaptive CMAC Backstepping Control

4.1. Ideal Backstepping Control. In this paper, the control goal is to make the position of the system able to track the given trajectory asymptotically stable signal. For achieving this goal, assume $f(x)$, $g(x)$, and $d(t)$ are known in (5); the steps of ideal backstepping method are as follows.

Step 1. Define position error:

$$e_1 = \theta_d - \theta, \tag{14}$$

where θ_d is input signal.

Define virtual control inputs:

$$\alpha = c_1 e_1 + \dot{\theta}_d, \tag{15}$$

where c_1 is a constant, which is greater than 0.

Step 2. Define

$$e_2 = \alpha - \dot{\theta}, \tag{16}$$

where $\dot{e}_2$ is

$$\dot{e}_2 = \dot{\alpha} - \ddot{\theta} = \dot{\alpha} - f(x) - g(x)u - d(t). \tag{17}$$

Step 3. Define Lyapunov function:

$$V_1 = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2, \tag{18}$$

where

$$\begin{aligned}
 \dot{V}_1 &= -c_1 e_1^2 + e_2 e_1 + e_2 \dot{e}_2 \\
 &= -c_1 e_1^2 + e_2 [e_1 + \dot{\alpha} - f(x) - g(x)u - d(t)].
 \end{aligned} \tag{19}$$

In order to make $\dot{V}_1 \leq 0$, the ideal backstepping controller is designed for

$$u_{IBC} = \frac{1}{g(x)} [\dot{\alpha} - f(x) - d(t) + e_1 + c_2 e_2], \quad (20)$$

where c_2 is a constant, which is greater than 0.

Put (20) into (19); it can get

$$\dot{V}_1 = -c_1 e_1^2 - c_2 e_2^2 \leq 0. \quad (21)$$

Thus, the asymptotic stability of the system can be guaranteed by the design of the control law.

4.2. SOWCB Design. Because the system is characterized by a heavy varying-load, slow time variation, nonlinearity, and uncertain disturbance, the ideal backstepping control algorithm is hard to get directly by (20). In order to solve this problem, in this paper, by using self-organizing wavelet adaptive CMAC control for an ideal to approximate backstepping controller, robust control is used to eliminate disturbance and approximation errors in the system; the control output can be shown as

$$u_{SOWCB} = u_{SOWC} + u_R, \quad (22)$$

where u_{SOWC} is self-organizing wavelet CMAC control; u_R is robust controller; u_{SOWCB} is SOWCB control.

Assume the optimal SOWC controller for an ideal to approximate backstepping controller, which is shown as

$$u'_{IBC} = u'_{SOWC} (\mathbf{I}, \mathbf{w}', \mathbf{a}', \mathbf{b}') = \mathbf{w}'^T \mathbf{r}' (\mathbf{a}', \mathbf{b}') + \varepsilon, \quad (23)$$

where ε is the minimum reconstruction error; $\mathbf{w}'$, $\mathbf{r}'$, $\mathbf{a}'$, and $\mathbf{b}'$ represent optimum parameter by $\mathbf{w}$, $\mathbf{r}$, $\mathbf{a}$, and $\mathbf{b}$; the optimal node is divided into two parts: the first part is the activation layer, including n_b node; the second part is the inactive parts, which include $n'_b - n_b$. The optimal parameters $\mathbf{w}'$, $\mathbf{r}'$, $\mathbf{a}'$, and $\mathbf{b}'$ can be divided into two parts, which is shown as

$$\begin{aligned} \mathbf{w}' &= \begin{bmatrix} \mathbf{w}'_e \\ \mathbf{w}'_i \end{bmatrix}; \\ \mathbf{a}' &= \begin{bmatrix} \mathbf{a}'_e \\ \mathbf{a}'_i \end{bmatrix}; \\ \mathbf{b}' &= \begin{bmatrix} \mathbf{b}'_e \\ \mathbf{b}'_i \end{bmatrix}; \\ \mathbf{r}' &= \begin{bmatrix} \mathbf{r}'_e \\ \mathbf{r}'_i \end{bmatrix}, \end{aligned} \quad (24)$$

where $\mathbf{w}'_e$, $\mathbf{r}'_e$, $\mathbf{a}'_e$, and $\mathbf{b}'_e$ are active part, respectively; $\mathbf{w}'_i$, $\mathbf{r}'_i$, $\mathbf{a}'_i$, and $\mathbf{b}'_i$ are inactive part, respectively.

Because the optimal SOWC is not easy to get, thus, get $\hat{u}_{SOWC}$ to approximate optimal value online. The control law equation (22) can be rewritten as

$$\begin{aligned} u_{SOWCB} &= \hat{u}_{SOWC} (\mathbf{I}, \hat{\mathbf{w}}_e, \hat{\mathbf{a}}_e, \hat{\mathbf{b}}_e) + u_R \\ &= \hat{\mathbf{w}}_e^T \hat{\mathbf{r}}_e (\hat{\mathbf{a}}_e, \hat{\mathbf{b}}_e) + u_R, \end{aligned} \quad (25)$$

where $\hat{\mathbf{w}}_e$, $\hat{\mathbf{a}}_e$, $\hat{\mathbf{b}}_e$, and $\hat{\mathbf{r}}_e$, respectively, are the optimal estimates of the parameters $\mathbf{w}'_e$, $\mathbf{a}'_e$, $\mathbf{b}'_e$, and $\mathbf{r}'_e$.

Put (25) into (23); the estimate error $\tilde{u}$ is shown as

$$\begin{aligned} \tilde{u} &= \mathbf{w}_e'^T \mathbf{r}_e' + \mathbf{w}_i'^T \mathbf{r}_i' + \varepsilon - \hat{\mathbf{w}}_e^T \hat{\mathbf{r}}_e - u_R \\ &= \tilde{\mathbf{w}}_e^T \mathbf{r}_e' + \hat{\mathbf{w}}_e^T \tilde{\mathbf{r}}_e + \mathbf{w}_i'^T \mathbf{r}_i' + \varepsilon - u_R, \end{aligned} \quad (26)$$

where $\tilde{\mathbf{w}}_e$ is $\mathbf{w}_e' - \hat{\mathbf{w}}_e$ and $\tilde{\mathbf{r}}_e$ is $\mathbf{r}_e' - \hat{\mathbf{r}}_e$.

Wavelet function becomes a part of the linear form [16], and, according to the Taylor series expansion, the $\tilde{\mathbf{r}}_e$ can be shown as

$$\begin{aligned} \tilde{\mathbf{r}}_e &= \begin{bmatrix} \tilde{r}_1 \\ \vdots \\ \tilde{r}_k \\ \vdots \\ \tilde{r}_{n_b} \end{bmatrix} \\ &= \begin{bmatrix} \left(\frac{\partial r_1}{\partial \mathbf{a}_e} \right)^T \\ \vdots \\ \left(\frac{\partial r_k}{\partial \mathbf{a}_e} \right)^T \\ \vdots \\ \left(\frac{\partial r_{n_b}}{\partial \mathbf{a}_e} \right)^T \end{bmatrix} (\mathbf{a}'_e - \hat{\mathbf{a}}_e) + \begin{bmatrix} \left(\frac{\partial r_1}{\partial \mathbf{b}_e} \right)^T \\ \vdots \\ \left(\frac{\partial r_k}{\partial \mathbf{b}_e} \right)^T \\ \vdots \\ \left(\frac{\partial r_{n_b}}{\partial \mathbf{b}_e} \right)^T \end{bmatrix} (\mathbf{b}'_e - \hat{\mathbf{b}}_e) \\ &\quad + \mathbf{O}_t = \mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e + \mathbf{O}_t, \end{aligned} \quad (27)$$

where $\tilde{\mathbf{a}}_e$ is $\mathbf{a}'_e - \hat{\mathbf{a}}_e$; $\tilde{\mathbf{b}}_e$ is $\mathbf{b}'_e - \hat{\mathbf{b}}_e$; $\mathbf{O}_t$ is vector of the higher order term.

Equation (27) of $\partial r_k / \partial \mathbf{a}_e$ and $\partial r_k / \partial \mathbf{b}_e$ can be defined as

$$\begin{aligned} \left[\frac{\partial r_k}{\partial \mathbf{a}_e} \right]^T &= \left[\underbrace{0, \dots, 0}_{(k-1) \times n_a}, \frac{\partial r_k}{\partial a_{1k}}, \dots, \frac{\partial r_k}{\partial a_{n_a k}}, \underbrace{0, \dots, 0}_{(n_b - k) \times n_a} \right], \\ \left[\frac{\partial r_k}{\partial \mathbf{b}_e} \right]^T &= \left[\underbrace{0, \dots, 0}_{(k-1) \times n_a}, \frac{\partial r_k}{\partial b_{1k}}, \dots, \frac{\partial r_k}{\partial b_{n_a k}}, \underbrace{0, \dots, 0}_{(n_b - k) \times n_a} \right]. \end{aligned} \quad (28)$$

Equation (27) can be rewritten as

$$\mathbf{r}'_e = \hat{\mathbf{r}}_e + \mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e + \mathbf{O}_t. \quad (29)$$

Put (27) and (29) into (26); it can get

$$\begin{aligned} \tilde{u} &= \tilde{\mathbf{w}}_e^T (\hat{\mathbf{r}}_e + \mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e + \mathbf{O}_t) \\ &\quad + \hat{\mathbf{w}}_e^T (\mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e + \mathbf{O}_t) + \mathbf{w}_i'^T \mathbf{r}_i' + \varepsilon - u_R \\ &= \tilde{\mathbf{w}}_e^T \hat{\mathbf{r}}_e + \tilde{\mathbf{w}}_e^T (\mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e) + \xi - u_R, \end{aligned} \quad (30)$$

where the approximate error ξ is shown as

$$\xi = \tilde{\omega}_e^T \mathbf{r}_a^T \tilde{\mathbf{a}}_e + \tilde{\omega}_e^T \mathbf{r}_b^T \tilde{\mathbf{b}}_e + \omega_e'^T \mathbf{O}_t + \omega_i'^T \mathbf{r}_i' + \varepsilon. \quad (31)$$

Substitute (20) and (30) into (17); it can get

$$\begin{aligned} \dot{e}_2(t) &= \dot{\alpha}(t) - f(x, t) - g(x, t) - d(x, t) \\ &= g(x)(u_{IBC} - u) - c_2 e_2(t) - e_1(t) \\ &= g(x)\tilde{u} - c_2 e_2(t) - e_1(t) \\ &= g(x) \left[\tilde{\omega}_e^T \hat{\mathbf{r}}_e + \tilde{\omega}_e^T (\mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e) + \xi - u_R \right] \\ &\quad - c_2 e_2(t) - e_1(t). \end{aligned} \quad (32)$$

To set up the system of adaptive parameter,

$$\dot{\tilde{\omega}}_e = \eta_1 e_2(t) \hat{\mathbf{r}}_e, \quad (33)$$

$$\dot{\tilde{\mathbf{a}}}_e = \eta_2 e_2(t) \mathbf{r}_a \tilde{\omega}_e, \quad (34)$$

$$\dot{\tilde{\mathbf{b}}}_e = \eta_3 e_2(t) \mathbf{r}_b \tilde{\omega}_e, \quad (35)$$

where η_1, η_2, η_3 are positive constants. Self-organizing wavelet adaptive CMAC backstepping control is shown in Figure 3.

The robust compensator is designed as [10, 17]

$$u_R = \frac{\rho^2 + 1}{2\rho^2} e_2(t), \quad (36)$$

where ρ is a positive constant.

Define Lyapunov function

$$V_2 = V_1 + \frac{1}{2\eta_1} \tilde{\omega}_e^T \tilde{\omega}_e + \frac{1}{2\eta_2} \tilde{\mathbf{a}}_e^T \tilde{\mathbf{a}}_e + \frac{1}{2\eta_3} \tilde{\mathbf{b}}_e^T \tilde{\mathbf{b}}_e. \quad (37)$$

According to (37) and (32), the $\dot{V}_2$ can be shown as

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + \frac{1}{\eta_1} \tilde{\omega}_e^T \dot{\tilde{\omega}}_e + \frac{1}{\eta_2} \tilde{\mathbf{a}}_e^T \dot{\tilde{\mathbf{a}}}_e + \frac{1}{\eta_3} \tilde{\mathbf{b}}_e^T \dot{\tilde{\mathbf{b}}}_e = -c_1 e_1^2(t) \\ &\quad + e_1(t) e_2(t) + e_2(t) \dot{e}_2(t) + \frac{1}{\eta_1} \tilde{\omega}_e^T \dot{\tilde{\omega}}_e + \frac{1}{\eta_2} \tilde{\mathbf{a}}_e^T \dot{\tilde{\mathbf{a}}}_e \\ &\quad + \frac{1}{\eta_3} \tilde{\mathbf{b}}_e^T \dot{\tilde{\mathbf{b}}}_e = -c_1 e_1^2(t) + e_1(t) e_2(t) + e_2(t) \\ &\quad \cdot \left[(\tilde{\omega}_e^T \hat{\mathbf{r}}_e + \tilde{\omega}_e^T (\mathbf{r}_a^T \tilde{\mathbf{a}}_e + \mathbf{r}_b^T \tilde{\mathbf{b}}_e) + \xi - u_R) \right. \\ &\quad \left. - c_2 e_2(t) - e_1(t) \right] + \frac{1}{\eta_1} \tilde{\omega}_e^T \dot{\tilde{\omega}}_e + \frac{1}{\eta_2} \tilde{\mathbf{a}}_e^T \dot{\tilde{\mathbf{a}}}_e + \frac{1}{\eta_3} \tilde{\mathbf{b}}_e^T \dot{\tilde{\mathbf{b}}}_e \\ &= -c_1 e_1^2(t) - c_2 e_2^2(t) + \tilde{\omega}_e^T \left[e_2(t) \hat{\mathbf{r}}_e - \frac{1}{\eta_1} \dot{\tilde{\omega}}_e \right] \\ &\quad + \tilde{\mathbf{a}}_e^T \left[e_2(t) \hat{\mathbf{r}}_a \tilde{\omega}_e - \frac{1}{\eta_2} \dot{\tilde{\mathbf{a}}}_e \right] + \tilde{\mathbf{b}}_e^T \left[e_2(t) \hat{\mathbf{r}}_b \tilde{\omega}_e \right. \\ &\quad \left. - \frac{1}{\eta_3} \dot{\tilde{\mathbf{b}}}_e \right] + e_2(t) [\xi - u_R]. \end{aligned} \quad (38)$$

FIGURE 3: Self-organizing wavelet CMAC adaptive backstepping control.

Put (33)~(36) into (38); it can get

$$\begin{aligned} \dot{V}_2 &= -c_1 e_1^2(t) - c_2 e_2^2(t) + e_2(t) \xi - e_2(t) u_R \\ &= -c_1 e_1^2(t) - c_2 e_2^2(t) - \frac{1}{2} e_2^2(t) - \frac{1}{2} \left[\frac{e_2(t)}{\rho} - \rho \xi \right]^2 \\ &\quad + \frac{1}{2} \rho^2 \xi^2 \leq -\frac{1}{2} e_2^2(t) + \frac{1}{2} \rho^2 \xi^2. \end{aligned} \quad (39)$$

Assume $\xi \in [0, T], \forall T \in [0, \infty)$; then

$$V_2(T) - V_2(0) \leq -\frac{1}{2} \int_0^T e_2^2(t) dt + \frac{1}{2} \rho^2 \int_0^T \xi^2 dt. \quad (40)$$

When $V(T) \geq 0$, put (37) into (40); it can get

$$\begin{aligned} \int_0^T e_2^2(t) dt &\leq \mathbf{e}^T(0) \mathbf{e}(0) + \frac{1}{\eta_1} \tilde{\omega}_e^T(0) \tilde{\omega}_e(0) \\ &\quad + \frac{1}{\eta_2} \tilde{\mathbf{a}}_e^T(0) \tilde{\mathbf{a}}_e(0) + \frac{1}{\eta_3} \tilde{\mathbf{b}}_e^T(0) \tilde{\mathbf{b}}_e(0) \\ &\quad + \rho^2 \int_0^T \xi^2 dt. \end{aligned} \quad (41)$$

When the initial condition parameters $\mathbf{e}(0)$, $\tilde{\omega}_e(0)$, $\tilde{\mathbf{a}}_e(0)$, and $\tilde{\mathbf{b}}_e(0)$ are assumed to be zero, the tracking performance of the system is represented as

$$\int_0^T e_2^2(t) dt \leq V_2(0) - V_2(\infty). \quad (42)$$

Thus, according to the Barbalat lemma [18], the output of the system can be gradual tracking command signal and stable.

5. Simulation Result and Analysis

The main parameters in the AC system were as follows: the friction coefficient of the system is $B = 1.43 \times 10^{-4} \text{ N}\cdot\text{m}/(\text{rad}\cdot\text{s}^{-1})$; system load rotational inertia: $J = 8200 \text{ kg}\cdot\text{m}^2$; system load disturbing moment: $93200 \text{ kg}\cdot\text{m}^2$;

FIGURE 4: Step response curve of load disturbance.

FIGURE 6: The moment of inertia changes step response curve.

FIGURE 5: The initial moment of inertia of step response curve.

FIGURE 7: Tracking error curve of the system.

friction moment of the load: $850 \text{ kg}\cdot\text{m}^2$; reduction ratio: $i = 1002$; motor torque coefficient $K_t = 0.195 \text{ N}\cdot\text{m/A}$; and choose initial node $n_b = 1$. The initial parameter is set to the wavelet function: $a_{i1} = 0$, $b_{i1} = 1.2$. Select input layer in wavelet CMAC $n_a = 2$; self-organizing wavelet CMAC adaptive backstepping controller parameter selection for $\eta_1 = 0.5$, $\eta_2 = 0.1$, $\eta_3 = 0.1$, $\rho = 0.2$, $c_1 = 0.3$, $m_{th} = 0.5$, $\beta_{th} = 0.01$, and $\tau = 0.01$.

In order to test and verify the effectiveness of the self-organization wavelet adaptive CMAC backstepping control, adaptive CMAC controller is used to compare it. The simulation results are as shown in Figures 4–8.

Figure 4 shows the position response curve added with a 85 Nm step disturbance at 3 s .

As it can be seen from Figure 4, when there is a load disturbance, using CMAC adaptive control algorithm in response to a larger location offset occurs, and it needs 0.83 s to recover the reference position; however, using self-organizing wavelet adaptive CMAC backstepping control

FIGURE 8: The structure of the node curve.

FIGURE 9: Schematic of the semiphysical simulation platform.

(a)

(b)

FIGURE 10: Photograph of the semiphysical simulation platform.

algorithm, the system has better suppression performance of load disturbance, and only 0.45 s can be stabilized.

Figure 5 shows the position of the initial moment of inertia of the response curve; Figure 6 for the moment of inertia is a variation of the initial value to 1.5 times the position of the response curve.

As can be seen from Figures 5 and 6, when the rotational inertia of the system is as the initial value, there is no overshoot in Figures 5 and 6, using CMAC adaptive control system when the arrival time of the steady state is longer than the required self-organizing adaptive CMAC wavelet backstepping. When the moment of inertia changes, using adaptive CMAC control system to produce the overshoot, and the system required to reach steady state time is 4.52 s, the self-organizing wavelet CMAC adaptive backstepping control is "SOWCB" control, with faster system response time, the time required to reach a steady state is 1.31 s, and the system has better robustness to the change of parameters.

Figure 7 shows a system of sine-input signal tracking error curve; Figure 8 is a node change through self-organization training process from the initial value of 1 to 4 stable nodes.

Figure 7 shows that using adaptive CMAC control system of the maximum tracking error is 0.146 degrees, and,

using the self-organizing wavelet CMAC adaptive backstepping control, the maximum tracking error is only 0.0156 degrees. It shows that with the parameter uncertainty in the system and the presence of external disturbances, self-organization designed CMAC adaptive wavelet inversion controller enables the rapid tracking of servo system given position signals and by introducing more efficient robust control suppresses the system impact of various uncertainties, to improve the accuracy and robustness of the system.

6. Semiphysical Simulation Test

To investigate the efficiency of the proposed self-organizing wavelet adaptive CMAC backstepping control as a strategy in establishing AC servo system, a semiphysical simulation platform is constructed to simulate the working conditions of the servo control system. The test results were compared to verify the performance of the controller in this paper superiorly.

The semiphysical simulation test-bed structure diagram and object diagram are as shown in Figures 9 and 10, respectively. Based on the components shown in Figure 9, the platform consists of seven parts, including the control computer, the sensor system for measurement, the power

FIGURE 11: System step response tracking error.

amplifier (PA), the precision reduction gearbox (PRG), the loading fixture (LF), the actuating motor (AM), and the test bed. The loading fixture, which consists of the rotational inertia plate (RIP) and the magnetic powder brake (MPB), is employed for the simulation of the rotational inertia, the load torque, and the frictional resistance moment. The rotational inertia variations in the loads are well simulated by changing the RIP. Similarly, the variations in the load torque and the frictional resistance moment are also well simulated by controlling the output torque of the MPB.

To investigate the tracking accuracy of the servo system with adaptive self-organizing wavelet CMAC backstepping control system, sinusoidal command tracking with a frequency of 1 Hz and amplitude of 100 degrees is conducted on the semiphysical simulation platform. The corresponding tracking errors of both the SOWCB and adaptive CMAC control systems are illustrated in Figure 11.

The figure also illustrates that the SOWCB control system has a smaller steady-state error and external disturbance error showed stronger inhibitory action and has faster response speed and good robustness.

7. Conclusions

In this paper, due to the existence of nonlinear servo system problem, self-organizing CMAC adaptive wavelet backstepping control methods have been proposed. The simulation and prototype test results showed that

- (1) compared to self-organization wavelet algorithm with the traditional CMAC method, it has higher accuracy;
- (2) the scheme of system uncertainties and external disturbance has strong robustness and good dynamic and steady-state response performance.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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