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Synchronous Control of Hysteretic Creep Chaotic Neural Network

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ABSTRACT A chaotic neuron with hysteretic and creep characteristics is proposed based on the conventional chaotic neuron model, with which a neural network is constructed, and the synchronous control between the hysteretic creep chaotic neuron or neural network and the deterministic chaotic neuron or neural network is investigated by the sliding mode control. The hysteretic activation function of the neuron is constructed by shifting the sigmoid function. The hysteretic parameters have creep properties, which lead to the uncertain responses of the neurons. The equivalent sliding mode control law can be designed according to the error equation of the synchronous system, and the Lyapunov method is used to prove the stability of the system. Furthermore, fuzzy sliding mode control law is designed to restrain the chattering, to reduce the synchronous error, as well as to shorten the transition time. The validity of this method has been proved by simulation experiments.

INDEX TERMS Hysteresis, creep, chaos, neural networks, synchronous.

I. INTRODUCTION

Artificial neural network is a model of information processing which is constructed basing on mimicking natural biological neural system. It shows good application performance in many engineering fields. Owing to the complexity of the biological nervous system, the current artificial neural networks almost ignored a lot of nonlinear characteristics in the biological nervous system.

Over the past decades, the development of neural network has reached a relatively mature stage. Many engineering problems can be resolved by neural networks and many theories are also used to improve the performance of the neural network. In order to improve the information processing ability of the network, the nonlinear characteristics of the biological nervous system are gradually incorporated into the artificial neural networks. Some artificial neural network models with compound nonlinear characteristics are constructed, and the performances of artificial neural networks are improved by using the nonlinear characteristic of the natural biological neural system. Chaotic neural network [1]–[3], a typical network model combining the characteristics of chaos, has shown unique performances in the field of optimization calculation, pattern recognition and associative memory by its searching ability of chaos [4]–[6]. Basing on this function, the hysteretic chaotic neural network is constructed by the combination of the hysteretic behavior of the biological nervous system, and the hysteretic chaotic neural network can further improve the performance of the network [7], [8]. Furthermore, the creep characteristics in biological neurons have also been noticed [9]–[11]. During the realization of the neural network by hardware, some drift response of the hardware chip or circuit must be caused, which leads to the uncertainty of the circuit parameters, because of the change of the environmental temperature or other conditions. Because the hysteretic and creep characteristics can make the chaotic neural network have more complicated dynamic behaviors, it has a good application prospect in the secure communication. The synchronous control is the basis to apply the chaotic system to perform the secure communication [12]–[14]. Synchronous control of the chaotic neural network plays a significant role in secure communication [15]. In the past decade, nonlinear science has been developed promptly. A lot of research achievements provide important theoretic tools for studying the synchronous control of chaotic systems. Although, there are some methods which can be used to perform the synchronization of chaotic neural networks, most of them focus on the synchronous control of deterministic chaotic neural network system, and often ignore the uncertanty of the parameter. In addition, the synchronous control problem on the chaotic neural networks with the same structure is often investigated. However, in fact, it is difficult to design or build two identical networks. Therefore, it has important practical significance to do the study on the synchronization problem of uncertain neural networks with the different structure. Understandably, in this case, the synchronization problem will become more difficult and complex.

Therefore, in order to improve the physical realization, a novel chaotic neural network model with hysteresis and creep is constructed by combing the hysteretic and creep characteristic into the traditional chaotic neural network. And the synchronous control problem between the traditional deterministic chaotic neural network and the novel network is investigated by the sliding mode control method. Compared with the existing neural networks, the neural network proposed in this paper contains more nonlinear and uncertain factors, so it is easier to be implemented in engineering.

In Section II, the uncertainty neuron and neural network model with the hysteretic and creep characteristics are given. And their dynamic behaviors are investigated. In Section III, the synchronous control of neuron and neural network are performed by the sliding mode control. And the chattering is restrained by the fuzzy inference. In Section IV, simulation results are given to prove the validity of the method. A brief conclusion is given in Section V.

II. NOVEL NEURON AND NEURAL NETWORK MODEL

When adding the self-feedback in traditional Hopfield neural network, the neuron or neural network could show the chaotic behaviors. In this way, the chaotic neural network model can be constructed, for instance, the transient chaotic neuron or neural network.

The mathematical model of the conventional deterministic chaotic neuron can be described as:

$$y(k+1) = py(k) - \alpha\,[x(k) - I_0] \tag{1}$$

$$x(k) = f\,[y(k)] \tag{2}$$

$$f(s) = \left[1 + \exp(-c \cdot s)\right]^{-1} \tag{3}$$

Where, $x(k)$ and $y(k)$ are the output of neuron and the inner state of neuron at discrete time t, the coefficient $p > 0$, I_0 is the input bias of neuron, α is the self-feedback gain coefficient, the function $f(\,)$ is the activation function which is often chosen as the Sigmoid function.

The bifurcation diagram and the Lyapunov exponent diagram of the neuron with the parameters $p = 1.0$, $I_0 = 0.86$, $c = 250$ are shown in Fig.1 and Fig.2.

From Fig.1, with the increase of α, the neuron becomes the chaos state through the period doubling bifurcation. The positive Lyapunov exponent implies the occurrence of chaos in Fig.2.

Considering the hysteretic characteristics in the response of the natural biological nervous system [7], [8], the hysteretic characteristic can be introduced into the neurons by changing the activation function as the function with the hysteretic response. The hysteretic activation function can be described

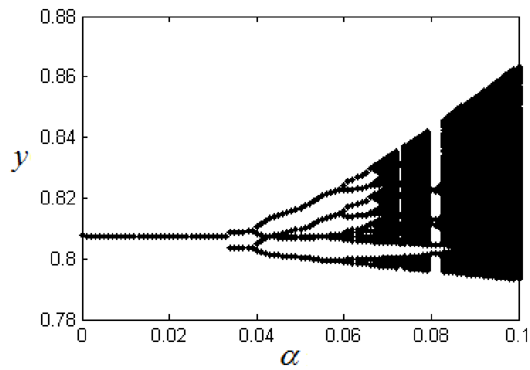

FIGURE 1. The bifurcation diagram.

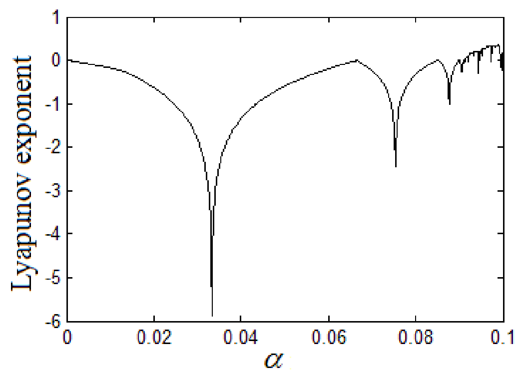

FIGURE 2. Lyapunov exponent diagram.

as follows:

$$f_c(s) = \begin{cases} (1+\exp[-c(s-a)])^{-1}, & \Delta s(k) > 0 \\ (1+\exp[-c(s+a)])^{-1}, & \Delta s(k) < 0 \end{cases} \tag{4}$$

$$\Delta s(k) = s(k) - s(k-1) \tag{5}$$

Where, a is the hysteretic parameter of the neuron activation response which forms a hysteretic loop in the interval $(-\infty, +\infty)$, the neuron can give out different response according to the rise or fall of the input state trend. Compared with the conventional neuron, the hysteretic response of the neuron not only enhances the ability of the neuron to maintain the original state, but also increases the complexity of the nonlinear behavior of the neuron.

Set $p = 1.0$, $I_0 = 0.86$, $c = 250$, $\alpha = 0.098$, the Lyapunov exponent diagrams changes with the different hysteretic parameter can be shown in Fig.3.

According to the Fig.3, the chaotic characteristic of the neuron has a good robustness to the change of the hysteretic parameters, that is, neurons can be always in the chaotic state when the hysteretic parameters are changed in a large range. Furthermore, when there is the creep characteristic in the hysteretic parameter, the activation function can be described as:

$$f_{cr}(s, \Delta r) = \begin{cases} (1+\exp[-c(s-a+\Delta r)])^{-1}, & \Delta s(k) > 0 \\ (1+\exp[-c(s+a+\Delta r)])^{-1}, & \Delta s(k) < 0 \end{cases} \tag{6}$$

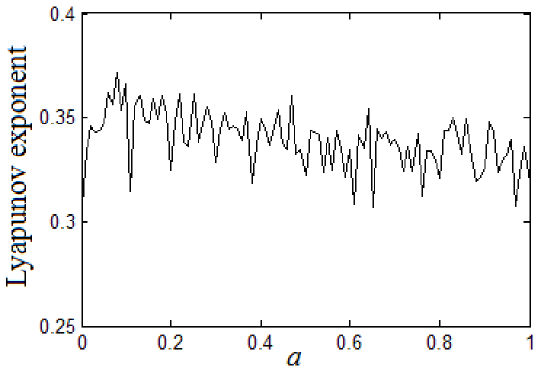

FIGURE 3. Lyapunov exponent with different hysteretic parameter.

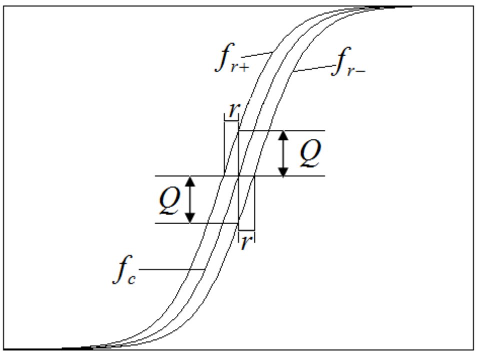

FIGURE 4. Hysteretic creep excitation function.

Where Δr is the creep parameter, $\Delta r \in [-r, +r]$, $r > 0$ is the creep amplitude. Some uncertainty can be caused in the hysteretic response of neuron by the creep characteristic. For instance, in Fig.4, the uncertain response f_{cr} betweens f_{r-} and f_{r+} will be output for the input s, that is $f_{cr} \in [f_{r-}, f_{r+}]$. Thus, the uncertain response of the neuron D is caused by the creep characteristic.

$$D = f_{cr}(s, \Delta r) - f_c(s) \tag{7}$$

According to the Fig.4, Q is the upper boundary of the uncertainty D, that is $|D| \leq Q$, Q is the maximum amplitude of the output response of the neuron due to the creep.

Various of neural network models can be obtained by the different coupling way of the neurons above. For instance, the mathematical model of the deterministic chaotic neural network can be described as follows:

$$x_i(k) = f\,[y_i(k)] \tag{8}$$

$$y_i(k+1) = py_i(k) + \beta\left[\sum_{j=1, j\neq i}^{n} w_{ij}x_j(k) + I_i\right] - \alpha\,[x_i(k) - I_0] \tag{9}$$

Where the parameter β is the coupling coefficient among the neurons, and w_{ij} is the weight between neuron i and neuron j. Correspondingly, the chaotic neural network model with the hysteresis and creep can be shown as:

$$X_i(k) = f_{cr}\,[Y_i(k)] \tag{10}$$

$$Y_i(k+1) = pY_i(k) + \beta\left[\sum_{j=1, j\neq i}^{n} w_{ij}X_j(k) + I_i\right] - \alpha\,[X_i(k) - I_0] \tag{11}$$

III. SYNCHRONOUS CONTROL OF NEURON AND NEURAL NETWORK

In this paper, the synchronous control of chaotic neural networks with hysteretic and creep is investigated. That is, the synchronization between the deterministic chaotic neural network and hysteretic chaotic neural network with the creep uncertainty can be perfomed by the sliding mode control law.

A. SYNCHRONOUS CONTROL OF NEURON

The deterministic chaotic neuron model defined in Eq.(1)-(3) can be described as:

$$y(k+1) = py\,(k) - \alpha\,[f\,(y(k)) - I_0] \tag{12}$$

The chaotic neuron model with hysteresis and creep uncertainty can be described as:

$$Y(k+1) = pY\,(k) - \alpha\,[f_{cr}(Y(k), \Delta r) - I_0] \tag{13}$$

Its controlled model can be described as:

$$Y(k+1) = pY\,(k) - \alpha\,[f_{cr}(Y(k), \Delta r) - I_0] + u(k) \tag{14}$$

Set $e(k)$ to be the synchronous errors between the two systems. It is defined as $e(k) = y(k) - Y(k)$.

The paper aims to design a control law $u(k)$ to make the inner states of the two systems above to do the synchronous motion. That is, when $k \to \infty$, $|y(k) - Y(k)| = |e(k)| \to 0$.

According to Eq.(12) and Eq.(13), the error equation of the system can be described as:

$$\begin{aligned} e(k+1) &= pe(t) - \alpha[f\,(y(k)) - f_{cr}(Y(k))] - u(k) \\ &= pe(k) - \alpha[f\,(y(k)) - f_c(Y(k))] + \alpha \cdot D - u(k) \end{aligned} \tag{15}$$

Set $\phi[e(k)] = f\,[y(k)] - f_c[Y(k)]$, then,

$$e(k+1) = pe(k) - \alpha \cdot \phi[e(k)] + \alpha \cdot D - u(k) \tag{16}$$

There are the structure differences between the two neurons, and the parameter creeping in the activation function can lead to the uncertainty of the output response, so the equivalent sliding mode control is chosen to perform the synchronous control.

Define the sliding surface as:

$$s(k) = he(k) + de(k) \tag{17}$$

Where, $h > 0$ meets Hurwitz condition[16], $de(k) = [e(k) - e(k-1)]/t_s$, t_s is the sampling time. Therefore, $de(k+1) = [e(k+1) - e(k)]/t_s$. Then,

$$s(k+1) = (h + 1/t_s)e(k+1) - e(k)(1/t_s) \tag{18}$$

When the system enters the ideal sliding mode, it should be satisfied:

$$s(k+1) = s(k) \tag{19}$$

That is,

$$(h + 1/t_s)e(k+1) - e(k)\cdot 1/t_s = h\cdot e(k) + de(k) \tag{20}$$

Then,

$$e(k+1) = \frac{e(k)(h+1/t_s) + de(k)}{h+1/t_s} \tag{21}$$

Therefore, without considering the uncertainty caused by the creep, the equivalent control law $u_{eq}(k)$ can be resolved as:

$$\begin{aligned} u_{eq}(k) &= pe(k) - \alpha\cdot\phi[e(k)] - e(k+1) \\ &= pe(k) - \alpha\cdot\phi[e(k)] - \frac{e(k)\cdot(h+1/t_s) + de(k)}{h+1/t_s} \end{aligned} \tag{22}$$

$u_{sw}(k)$ can be designed as:

$$u_{sw}(k) = Ksgn(s) = (\alpha\cdot Q + \eta)sgn(s) \tag{23}$$

Then $u(k) = u_{eq}(k) + u_{sw}(k)$, that is,

$$\begin{aligned} u(k) &= pe(k) - \alpha\cdot\phi\,[e(k)] - e(k) \\ &\quad - de(k)/(h+1/t_s) + (\alpha\cdot Q + \eta)sgn(s) \end{aligned} \tag{24}$$

A Lyapunov function can be chosen as:

$$V(k) = s^2(k) \tag{25}$$

$$\begin{aligned} s(k+1) &= (h+1/t_s)e(k+1) - e(k)/t_s \\ &= s(k) - (h+1/t_s)[u_{sw}(k) + \alpha\cdot D] \end{aligned} \tag{26}$$

Thus,

$$\begin{aligned} &V(k+1) - V(k) \\ &\quad = s^2(k+1) - s^2(k) \\ &\quad = (h+1/t_s)\{(h+1/t_s)[(\alpha\cdot Q+\eta)\cdot sgn(s) + \alpha\cdot D]^2 \\ &\qquad - 2s(k)[(\alpha\cdot Q+\eta)\cdot sgn(s) + \alpha\cdot D]\} \end{aligned} \tag{27}$$

If $0 < \eta < \frac{2|s|}{h+1/t_s} - 2\alpha\cdot Q$,

$$V(k+1) - V(k) < 0 \tag{28}$$

Hereby, the reachability of the sliding surface can be proved. Because the sliding surface meets the Hurwitz condition, the stability of the system has also been proved.

B. SYNCHRONOUS CONTROL OF NEURAL NETWORK

The deterministic chaotic neural network model defined by Eq. (8) and Eq. (9) can be described as:

$$\begin{aligned} y_i(k+1) &= py_i(k) + \beta\left[\sum_{j=1,j\neq i}^{n} w_{ij}\cdot f[y_j(k)] + I_i\right] \\ &\quad - \alpha\,[f[y_i(k)] - I_0] \end{aligned} \tag{29}$$

And the chaotic neural network model with the uncertainty of hysteresis and creep can be described as:

$$\begin{aligned} Y_i(k+1) &= pY_i(k) + \beta\left[\sum_{j=1,j\neq i}^{n} w_{ij}\cdot f_{cr}[Y_j(k)] + I_i\right] \\ &\quad - \alpha\,[f_{cr}[Y_i(k)] - I_0] \\ &= pY_i(k) + \beta\left[\sum_{j=1,j\neq i}^{n} w_{ij}\cdot f_c[Y_j(k)] + I_i\right] \\ &\quad - \alpha\,[f_c[Y_i(k)] - I_0] \\ &\quad + \beta\cdot\sum_{j=1,j\neq i}^{n} w_{ij}\cdot d_{ji} - \alpha\cdot d_{ii} \end{aligned} \tag{30}$$

Where, d_{ji} is the uncertainty of the neuron i casused by the neuron j. Set the whole uncertainty of the neuron i as $D_i = \beta\cdot\sum_{j=1,j\neq i}^{n} w_{ij}\cdot d_{ji} - \alpha\cdot d_{ii}$. Its upper bound is Q_i, that is $|D_i| \le Q_i$, then:

$$\begin{aligned} Y_i(k+1) &= pY_i(k) + \beta\left[\sum_{j=1,j\neq i}^{n} w_{ij}\cdot f_c[Y_j(k)] + I_i\right] \\ &\quad - \alpha\,[f_c[Y_i(k)] - I_0] + D_i \end{aligned} \tag{31}$$

Exert the control law $u_i(k)$ to Eq. (31) to make it keep synchronization with Eq. (29). That is,

$$\begin{aligned} Y_i(k+1) &= pY_i(k) + \beta\left[\sum_{j=1,j\neq i}^{n} w_{ij}\cdot f_c[Y_j(k)] + I_i\right] \\ &\quad - \alpha\,[f_c[Y_i(k)] - I_0] + D_i + u_i(k) \end{aligned} \tag{32}$$

Defined the error $e_i(k) = y_i(k) - Y_i(k)$, then,

$$\begin{aligned} e_i(k+1) &= pe_i(k) + \beta\cdot\sum_{j=1,j\neq i}^{n} w_{ij}\cdot\phi[e_j(k)] \\ &\quad - \alpha\cdot\phi[e_i(k)] - D_i - u_i(k) \end{aligned} \tag{33}$$

The sliding mode surface for each neuron is designed as $s_i(k) = h_i e_i(k) + de_i(k)$, The equivalent control law $u_{eqi}(k)$ can be designed as:

$$\begin{aligned} u_{eqi}(k) &= pe_i(k) - e_i(k) + \beta[\sum_{j=1,j\neq i}^{n} w_{ij}\cdot\phi(e_j(k))] \\ &\quad - \alpha\phi(e_i(k)) - de_i(k)/(h_i + 1/t_s) \end{aligned} \tag{34}$$

The switching control $u_{swi}(k)$ of each neuron can be designed as:

$$u_{swi}(k) = K_i sgn(s) = (Q_i + \eta_i)sgn(s_i) \tag{35}$$

Thus, the control law $u_i(k)$ of each neuron can be designed as:

$$u_i(k) = u_{eqi}(k) + u_{swi}(k) \tag{36}$$

The stability of the system can also be proved by Lyapunov method. A Lyapunov function is chosen as:

$$V(k) = \sum_{i=1}^{n} s_i^2(k) \tag{37}$$

Thus,

$$\begin{aligned} &V(k+1) - V(k) \\ &= \sum_{i=1}^{n} s_i^2(k+1) - \sum_{i=1}^{n} s_i^2(k) \\ &= \sum_{i=1}^{n} \left\{ \begin{array}{l} (h_i + 1/t_s)^2 \left[(Q_i + \eta_i)sgn(s_i(k)) + D_i\right]^2 \\ -2s_i(k)(h_i + 1/t_s)\left[(Q_i + \eta_i)sgn(s_i(k)) + D_i\right] \end{array} \right\} \end{aligned} \tag{38}$$

If $0 < \eta_i < \frac{2|s_i(k)|}{h_i + 1/t_s} - 2Q_i$,

$$V(k+1) - V(k) < 0 \tag{39}$$

Likewise, the reachability of the sliding surface can be proved. Because the sliding surface meets the Hurwitz condition, the stability of the system has also been proved.

C. REDUCING THE CHATTERING

It is inevitable that the equivalent sliding mode control of the above will cause the chattering phenomenon and synchronous error because the control state switches frequently in the process of controlling. In the initial stage, there is a large synchronous error between the two systems to be synchronized, the state of the controlled system is changed in a large range, and the uncertainty of the controlled system caused by the creep characteristics is large. The two systems can gradually approach the same after the control law lasts for a period of time. Because the movement of the chaotic system is bounded and the state of the controlled system acts only in the limited space of the drive system, the magnitude of the uncertainty caused by the creep parameter in the system is relatively small. Thus, the amplitude of the switching control can be reduced to effectively suppress the chattering, and the synchronous error of the system can also be reduced.

For this, the switching control law can be designed by the fuzzy inference.

$$u_{swi}(k) = K_i sgn(s) = \mu_i(k) \cdot (Q_i + \eta_i) sgn(s_i) \tag{40}$$

Where, $\mu_i(k)$ is fuzzy term of the switching control, which can be obtained by the fuzzy inference according to the synchronous error. The fuzzy inference system is designed as the single input and output form, and the membership degrees of the input error e and output term μ are shown in Fig. 5 and Fig. 6.

Fuzzy rules are designed as:

If ($e(k)$ is NB)then($\mu(k)$ is PB);

If ($e(k)$ is NS)then($\mu(k)$ is PS);

If ($e(k)$ is Z)then($\mu(k)$ is Z);

If ($e(k)$ is PS)then($\mu(k)$ is PS);

If ($e(k)$ is PB)then($\mu(k)$ is PB).

The center of gravity method is used to defuzzy the output variable μ.

According to the fuzzy control rules above, when the synchronous error is large, the state of the controlled system changes in a large range, and the value of uncertainty of the creep characteristic will be large, too. Therefore, the

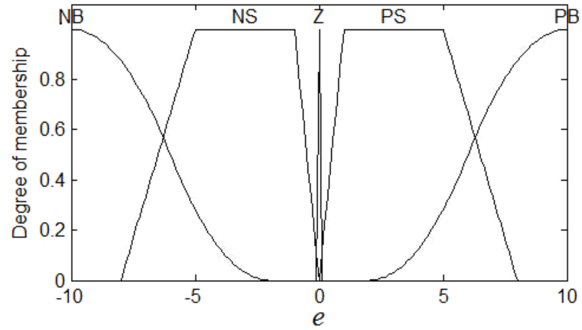

FIGURE 5. Membership Function of the input variable.

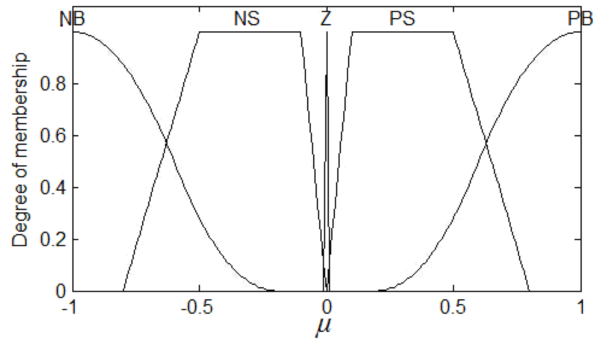

FIGURE 6. Membership Function of the output variable.

switching control coefficients are large, as well as the control effect. In this way, the system can move near the sliding surface. Hereafter, the state of the controlled system changes in a small limited space, and the uncertainty of the creep characteristic will be also in a small limited range. Thus, the switching control gradually reduces with the decrease of the synchronous error, and the chattering can be well restrained.

IV. SIMULATION EXPERIMENT

A. SYNCHRONIZATION OF NEURON

Set $p = 1.0$, $I_0 = 0.86$, $c = 250$, $\alpha = 0.098$, $a = 0.8$, $\Delta r \in [-0.001, +0.001]$, both the neurons are in the chaotic states. Set the initial states of two neurons as: $y(0) = 0.72$ and $Y(0) = -0.72$, the bound of the uncertainty caused by the creep properties is set as: $Q = 0.007$. Set the sliding mode parameter $h = 100$, and exert the control law $u(k)$ defined in Eq.(24) at $k = 30$, the error and its magnification are shown in Fig.7.

From Fig.7, the control law is exerted at the 30th step, the system gradually closes to the sliding mode and achieves synchronization at about the 100th step. Therefore, the control law designed in this paper can perform the synchronization of two neurons. Because it is a discrete system, it goes through the quasi-sliding mode surface ceaselessly, and the error is less than 2.5×10^{-3}.

The synchronous error and its magnification are obtained by the fuzzy sliding mode control are shown in Fig.8.

From Fig.8, the switching control can reduce gradually with the decrease of synchronous error, which can effectively restrain the chattering of sliding mode control.

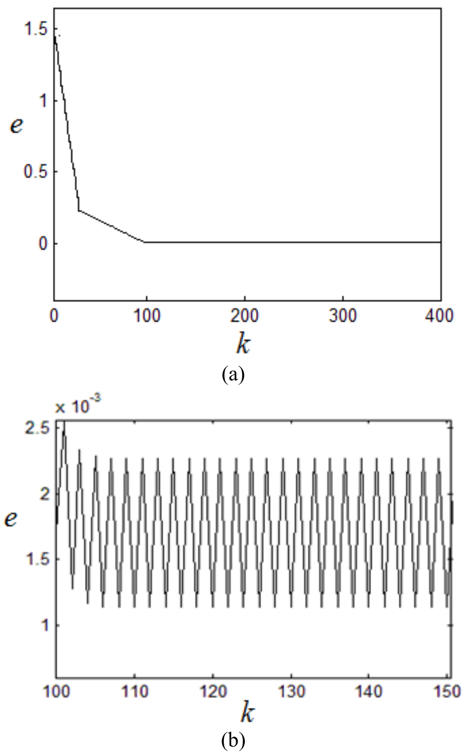

FIGURE 7. The synchronous error of equivalent sliding mode control. (a) The synchronous error. (b) The magnification of the synchronous error.

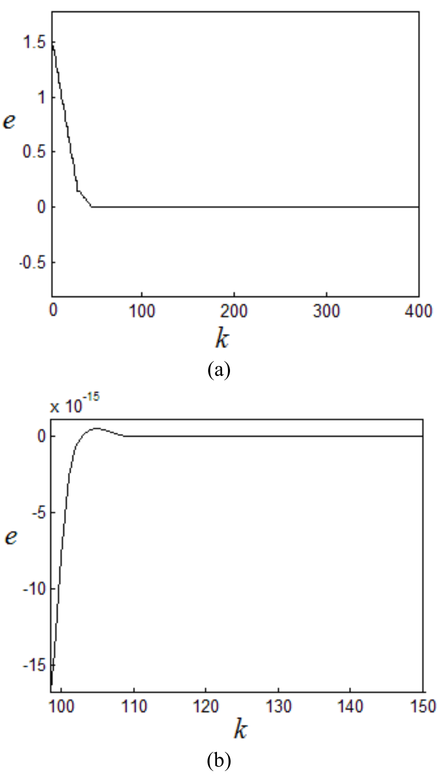

FIGURE 8. Neuron synchronous error of fuzzy sliding mode control. (a) Synchronous error graph. (b) Partial discharge graph.

The synchronous error is less than 10^{-15} which becomes significantly smaller, and the response speed of the system becomes significantly faster.

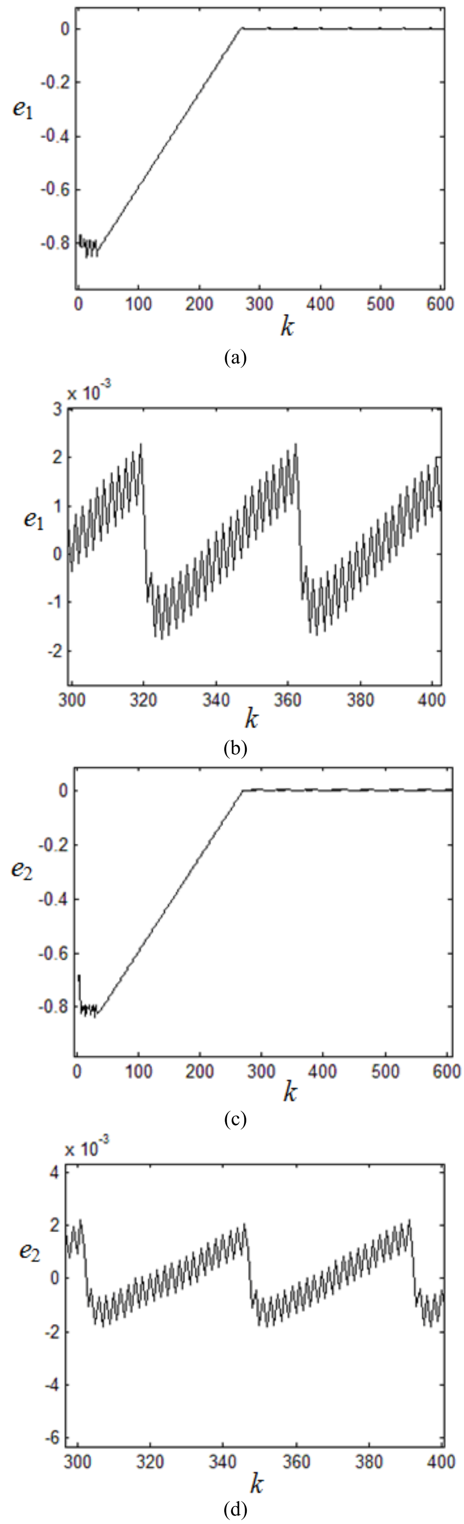

FIGURE 9. Synchronous errors between the neural networks obtained by the equivalent sliding mode control. (a) The synchronous error of the neuron 1. (b) The magnification of the synchronous error of the neuron 1. (c) The synchronous error of the neuron 2. (d) The magnification of the synchronous error of the neuron 2.

Thus it can be seen that the method proposed in this paper can perform the synchronous control of the chaotic neurons with the uncertain. And the fuzzy sliding mode control

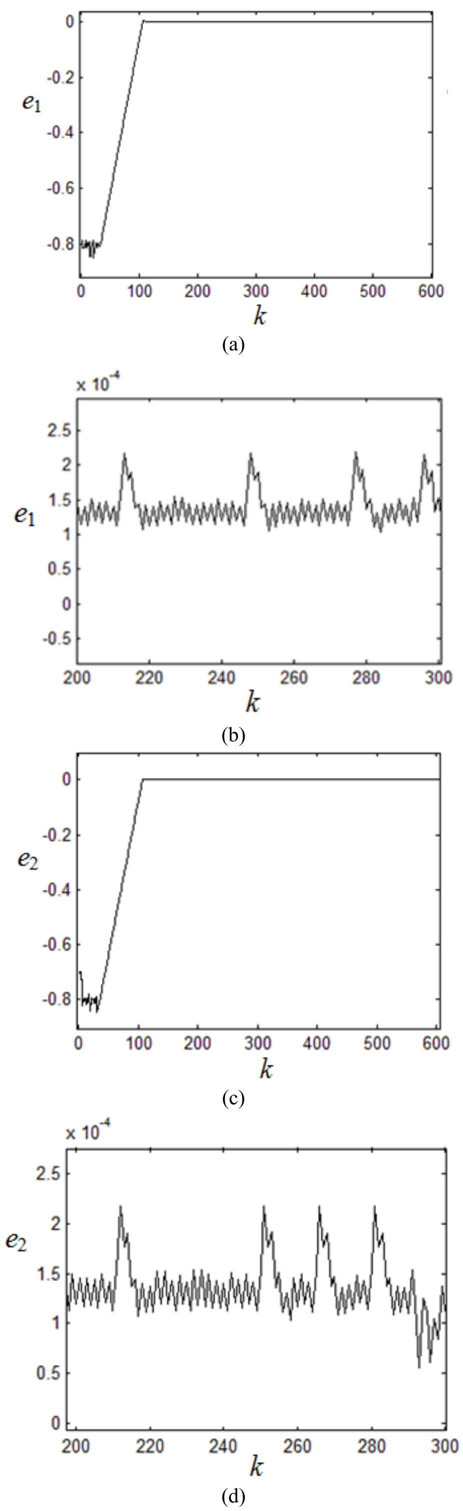

FIGURE 10. Synchronous errors between the neural networks obtained by the fuzzy sliding mode control. (a) The synchronous error of the neuron 1. (b) The magnification of the synchronous error of the neuron 1. (c) The synchronous error of the neuron 2. (d) The magnification of the synchronous error of the neuron 2.

can improve the control performance. On the one hand, the synchronous error can be reduced, on the other hand, the transition process is shortened.

B. SYNCHRONIZATION OF NEURAL NETWORK

A simple chaotic neural network is composed of two neurons. Set $I_1 = I_2 = 1.0$, the coupling coefficient $\beta = 0.001$, $w_{12} = w_{21} = 1.0$, $h_1 = h_2 = 100$, $y_1(0) = -0.01$, $y_2(0) = -0.005$, $Y_1(0) = 0.8$, $Y_2(0) = 0.7$. The control laws defined in Eq.(36) are exerted at $t = 30$, the synchronous errors and their magnifications between the chaotic neural network with the hysteretic and creep characteristics and the deterministic chaotic neural network are shown in Fig.9.

Although there is some coupling between the two neurons, their synchronous control can be performed. Therefore, the correctness and effectiveness of the method can be proved. However, the synchronous error becomes bigger, and the transition process becomes longer. The synchronization of the networks is achieved at about the 270th step.

The synchronous errors and their magnifications obtained by the fuzzy sliding mode control are shown in Fig.10.

From Fig.10, similarly, the synchronous error can be significantly reduced by the fuzzy sliding mode control. The response speed of the system becomes significantly faster, as well as the transition process is shorter, the synchronization of neural networks can be achieved at about 120th step.

Compared with the control strategy based on the filtered tracking error in [1], the fuzzy sliding mode control can restrain the uncertainty of internal parameters and the external disturbance, so the synchronous control between the uncertain chaotic neural network and the deterministic chaotic neural network can be performed.

In the practical physical systems, hysteretic characteristic and creep characteristic can represent some uncertainty and disturbance which would be generated in the physical implementation of the neural networks, such as some drift response of the hardware chip and the randomness of physical parameters distribution. Therefore, the neural network model proposed in this paper has the better realistic significance, and the synchronous control method proposed in this paper has better practicability in engineering.

V. CONCLUSION

A novel chaotic neural network model with hysteretic and creep characteristics is proposed in this paper. The sliding mode control method is used to perform the synchronous control between the uncertainty chaotic neural network with hysteretic and creep characteristics and the deterministic chaotic neural network. Furthermore, the fuzzy sliding mode control is designed to restrain the chattering. Simulation results prove the validity of the methods. Due to the good synchronous controllability and the enough small synchronous errors, the secure communication based on the uncertainty neural networks with different structures is the subsequent research direction and deserves our further exploration. Furthermore, the data-driven framework based on the neural network is considering to be constructed to perform the prediction analysis of the time series.

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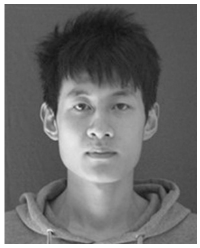

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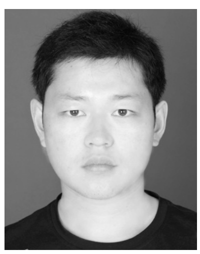

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