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Chaotic Adaptive Synchronization Control and Application in Chaotic Secure Communication for Industrial Internet of Things

TIEJUN WANG[1], DICONG WANG[2], AND KAIJUN WU[2]

[1]School of Mathematics and Computer Science Institute, Northwest University for Nationalities, Lanzhou 730030, China
[2]School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China

Corresponding author: Tiejun Wang (e-mail: wtj@mail.lzjtu.cn)

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ABSTRACT In this paper, a Lyapunov stability theorem is used to design a model system with adaptive control synchronization. The system uses the pseudo-randomness of chaotic signals to hide the signals that need to be transmitted in seemingly messy chaotic signals. The small input signals are superimposed on the chaotic signals, and the receiving end demodulates the useful information with a synchronized chaotic signal. The system can dynamically adjust the value of the controller according to the initial value of the neuron model so that the two coupling Hindmarsh–Rose neural system can be in a better synchronous state, with good stability and self-adaptability. In this paper, the controller is applied to chaotic secure communication. The simulation results verify the feasibility and effectiveness of the designed controller, and the capability of realizing the transmission of confidential information.

INDEX TERMS Chaotic adaptive synchronization, chaotic secure communication, coupled Hindmarsh–Rose (HR) neuron, industrial Internet of Things

I. INTRODUCTION

The nervous system is composed of billions of special cells called neurons. The efficient communication between these cells is critical to the normal functioning of the central and peripheral nervous systems [1]. To find out how the brain works or how to process information, it is necessary to clarify the basic processes and connections of nerve discharge activities, learn the specific cellular biological characteristics, and understand the various interpretations of neural circuit functions and brain function mechanism. Physiologists have also found that the phase synchronization of the rhythm of the heart and the rhythm of the respiration is produced by a weak bi-directional coupling. Synchronization is common in the nervous system, there are many physiological experiments and simulation studies have observed this phenomenon for industrial internet of things [2]–[4], so the study of neuronal synchronization has a very important practical significance.

Synchronization plays a very important role in the process of neural information. The synchronization of the neural information processing process is the basis for the brain to achieve the function of associative memory. The brain's treatment of nerve information is done through the neurons in different regions of the brain. Synchronization is a typical form of neuron cluster discharge activity. So synchronization is an important mechanism of neural information processing. Many neurological activities, such as selective attention, cognition, learning, memory, and some diseases are related to synchronization. The synchronization of cluster neurons is thought to play an important role in the treatment of Parkinson's disease, primary tremor and epilepsy [5]. Synchronization of neurons located in the sensory motor nucleus may result in resting tremor in Parkinson's disease [6]. The synchrotron discharge in the seizure appears to be from the tonic shot burst and the conversion activity [7]. The activation of the cortical region leads to surrounding trembling as a result of the presence of the synchronous discharge neuron clusters acting as pacemakers [8]. Therefore, the study the synchronous discharge activity of neurons has a very important physiological significance.

Since single neuron and coupling neuron is complex nonlinear systems and chaos are the inherent characteristics of nonlinear systems, so it is very necessary to study chaos synchronization [9]. In 1990, US Navy laboratory researchers Pecora and Carroll realized the synchronization of two chaotic systems for the first time [10], and with this breakthrough, making the application of chaos theory in the field of information possible. Then, on the basis of this, many scientists put forward a variety of synchronization and control theories and methods, such as active control method [11], feedback synchronization method [12], adaptive synchronization method [13], coupling synchronization method [14], [15], laser chaos control and synchronization [16]. In the transmission of confidential information, the use of chaos for information transmission has advantages such as strong confidentiality and anti-interference ability and so on. In particular, since the chaotic system has a high sensitivity to the initial conditions and system template parameters, so it is a natural candidate for the pseudo-random series, and can use the multimodality of the chaotic system to enhance the anti-decay and anti-interference robustness to provide important security guarantee for information transmission [17]–[19]. With the gradual and deep understanding of chaos, the application of chaos synchronization in confidential communication is becoming more and more perfect, and has become a hot field of current research.

In this paper, based on the Lyapunov stability theory, the Hindmarsh-Rose neuron discharge chaos model is selected as the object of study, and the adaptive analytic expression of coupled Hindmarsh-Rose neurons with unknown parameters is deduced. A nonlinear adaptive controller is designed to control the synchronization of the coupled Hindmarsh-Rose neurons with unknown parameters and then apply it to the chaotic security systems of two electrical synaptic coupled Hindmarsh–Rose (HR) neuron systems. The numerical simulation is used to prove and verify the feasibility and effectiveness of the control method proposed in this paper.

II. HINDMARSH-ROSE NEURON MODEL

The Hindmarsh-Rose neuron model is a data expression of snail neurons obtained by voltage clamp experiments. The neuronal model is a three-dimensional dynamic mathematical model [20] and it does not consider the role of a single ion channel formation on the neuronal cell membrane, but treats the neuronal cells as a whole. HR neuron model is simple and easy to implement, and can effectively simulate the repetitive and irregular behavior of molluscum neurons. It also has many neuronal behavioral characteristics such as periodic peak discharge, periodic cluster discharge, chaotic peak discharge and chaotic cluster discharge. It is a class of excitable neuron models, and HR neural models can be switched in multi-mode [21], so many experts and scholars use it as the ideal model to study the real neuronal discharge. The HR model used in this paper is a neuron model constructed by Krasimira Tsaneva-Atanasov which is similar to the Hindmarsh-Rose model [22]. Since the model is modified on the basis of the Hindmarsh-Rose model, and has the same dynamic behavior as the Hindmarsh-Rose model, so it is also known as the Hindmarsh-Rose model, referred to as HR

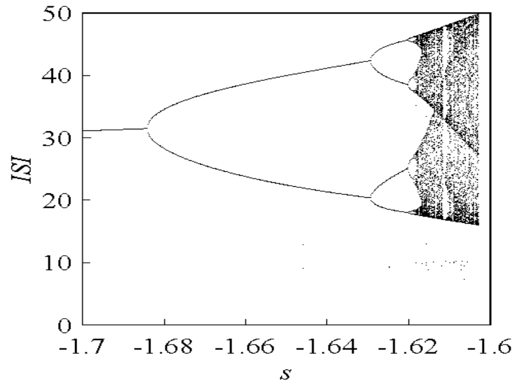

FIGURE 1. The diagram of inter-spike interval corresponding to the parameter s change.

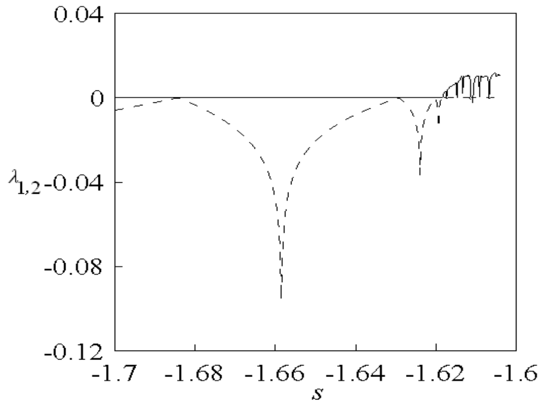

FIGURE 2. The Lyapunov exponential diagram corresponding to the parameter s change.

model. The expression is shown in equation (1).

$$\begin{cases} \dfrac{dx}{dt} = -s\left(-ax^3 + x^2\right) - y - bz \\ \dfrac{dy}{dt} = \varphi(x^2 - y), \\ \dfrac{dz}{dt} = \varepsilon(sa_1x_1 + b_1 - kz) \end{cases} \tag{1}$$

In the equation, x is the neuronal membrane voltage, y is the recovery variable associated with the current in the neuronal cell, z is the slow adaptability current, a, b, a_1, b_1, k, s are the parameters of the system, φ and ε are the parameters of the time scale control. The corresponding values are: $\varphi = 1$, $a = 0.5$, $b = 1$, $a_1 = -0.1$, $k = 0.2$. Refer to literature [22] for the detailed description of these parameters. When b1 $= -0.045$, make $\varepsilon = 0.02$, $b_1 = -0.0045$. Make the numerical simulation by changing the value of parameter s in the system, The diagram of inter-spike interval and **L**yapunov index are shown in FIGURE 1 and FIGURE 2 respectively.

It can be seen from FIGURE 1 that the value of s is in the range of $[-1.7, -1.6]$, and it is obvious that the system enters the final chaotic state from a simple one-cycle motion through period doubling bifurcation such as period 2, period 4 and period 8. It can be seen from FIGURE 2 that when the value of parameter s is -1.696, the system enters period 2 from single period through period doubling bifurcation, and when the value of the parameter s is -1.629, the system enters period 4 from period 2 through period doubling bifurcation. With the progressive increase of the value of parameter s, its value is in the range of $[-1.62, -1.6]$, and the corresponding maximum Lyapunov index is greater than zero, indicating that the system is in chaotic state at this time.

III. ADAPTIVE SYNCHRONIZATION CONTROL OF COUPLING HR NEURONS

For chaotic security systems, the design of linear feedback controller and the driving system parameters must be known in advance. However, in practical applications, it is difficult to obtain all the exact parameters of the driving system and response system, that is the choice of the appropriate controller value to ensure the stability of the synchronization error system often needs to cost a more energy and financial resources. Therefore, in order to overcome this drawback, this paper establishes a control method with adaptive synchronization to achieve the synchronization between the response system and the drive system in view of the existence of uncertain parameters in the system. The model expression is as follows:

$$\begin{cases} \dfrac{dx_1}{dt} = -s(-ax_1^3 + x_1^2) - y_1 - bz_1 + D(x_2 - x_1) \\ \dfrac{dy_1}{dt} = \varphi(x_1^2 - y_1) \\ \dfrac{dz_1}{dt} = \varepsilon(sa_1x_1 + b_1 - kz_1) \\ \dfrac{dx_2}{dt} = -s(-ax_2^3 + x_2^2) - y_2 - bz_2 \\ \qquad + D(x_1 - x_2) + (x_1 - x_2)Con \\ \dfrac{dy_2}{dt} = \varphi(x_2^2 - y_2) \\ \dfrac{dz_2}{dt} = \varepsilon(sa_1x_2 + b_1 - kz_2) \end{cases} \tag{2}$$

In the expression, D is the coupling coefficient, Con is the controller. The representative meanings and values of other parameters remain unchanged.

In order to verify whether the system achieves synchronization, we define the system synchronization difference as $e_0 = x_1 - x_2$, $e_1 = y_1 - y_2$, $e_2 = z_1 - z_2$, $e_3 = e_0 + e_1 + e_2$, then we can obtain:

$$\begin{cases} \dfrac{de_0}{dt} = sa(x_1^3 - x_2^3) - s(x_1^2 - x_2^2) \\ \qquad - (y_1 - y_2) - b(z_1 - z_2) - (2D + Con)(x_1 - x_2) \\ \dfrac{de_1}{dt} = \varphi((x_1^2 - x_2^2) - (y_1 - y_2)) \\ \dfrac{de_2}{dt} = \varepsilon sa_1(x_1 - x_2) - \varepsilon k(z_1 - z_2) \end{cases} \tag{3}$$

The Barbalat lemma: define $x : [0, +\infty) \to R$ has a first order continuous derivative, and $t \to +\infty$ has a limit, then if $\ddot{x}(t)$, and there is bounded $t \in [0, +\infty)$, then $\lim\limits_{t\to+\infty} x(t) = 0$.

According to Barbalat lemma, there are the following inferences:

If $x : [0, +\infty) \to R$ is consistent, and there is a limit to $t \to +\infty$, and there exists bounded $\lim\limits_{t\to\infty} \int_0^t e_i(\tau)d\tau$, $(i = 0, 1, 2)$, then $\lim\limits_{t\to+\infty} x(t) = 0$[23].

For any initial neuron model, design a suitable controller Con, if it is satisfied $\lim\limits_{t\to\infty} e_0(t) = 0$, $\lim\limits_{t\to\infty} e_1(t) = 0$, $\lim\limits_{t\to\infty} e_2(t) = 0$, then it can be explained that the two are synchronized.

Thus, construct Lyapunov function as follows:

$$V = \frac{1}{2}(e_0^2 + e_1^2 + e_2^2) \tag{4}$$

Then the derivative of V is:

$$\frac{dV}{dt} = e_0\frac{de_0}{dt} + e_1\frac{de_1}{dt} + e_2\frac{de_2}{dt} \tag{5}$$

Substitute it into the formula and we can obtain:

$$\begin{aligned} \frac{dV}{dt} &= se_0^2(a(x_1^2 + x_1x_2 + x_2^2) - (x_1 + x_2) \\ &\quad - (2D + Con)) - e_0e_1(1 - (x_1 + x_2)\varphi) \\ &\quad - e_0e_2(b - \varepsilon s) - e_1^2\varphi - \varepsilon ke_2^2 \end{aligned} \tag{6}$$

If $\frac{dV}{dt} < 0$, then it needs:

$$\begin{aligned} &se_0^2(a(x_1^2 + x_1x_2 + x_2^2) - (x_1 + x_2) \\ &\quad -(2D + Con)) - e_0e_1(1 - (x_1 + x_2)\varphi) \\ &\quad - e_0e_2(b - \varepsilon sa_1) - e_1^2\varphi - \varepsilon ke_2^2 < 0 \end{aligned} \tag{7}$$

Substitute $e_0 = x_1 - x_2$, $e_1 = y_1 - y_2$, $e_2 = z_1 - z_2$ it into the formula and we can obtain:

$$\begin{aligned} Con &> -2D + s(a(x_1^2 + x_1x_2 + x_2^2) - (x_1 + x_2)) \\ &\quad + \frac{(y_1 - y_2)}{(x_1 - x_2)}((x_1 + x_2)\varphi - 1) + \frac{(z_1 - z_2)}{x_1 - x_2}(\varepsilon sa_1 - b) \\ &\quad - \frac{(y_1 - y_2)^2}{(x_1 - x_2)^2}\varphi - \frac{(z_1 - z_2)^2}{(x_1 - x_2)^2}\varepsilon \mathrm{k} \end{aligned} \tag{8}$$

When it satisfy formula (8), then $\frac{dV}{dt} < 0$, and then, make

$$\begin{aligned} Con &= -2D + s(a(x_1^2 + x_1x_2 + x_2^2) - (x_1 + x_2)) \\ &\quad + \frac{(y_1 - y_2)}{(x_1 - x_2)}((x_1 + x_2)\varphi - 1) + \frac{(z_1 - z_2)}{x_1 - x_2}(\varepsilon sa_1 - b) \\ &\quad - \frac{(y_1 - y_2)^2}{(x_1 - x_2)^2}\varphi - \frac{(z_1 - z_2)^2}{(x_1 - x_2)^2}\varepsilon \mathrm{k} + 1, \end{aligned}$$

then we can know $\lim\limits_{t\to\infty} \int_0^t e_i(\tau)d\tau$, $(i = 0, 1, 2)$ exists and it is bounded. According to the *Lyapunov* stability theory, we can make $\frac{dV}{dt} < 0$ by adjusting the parameters, the error state e_0, e_1, e_2 and e_3 are asymptotically stable at the origin, that is, $\lim\limits_{t\to\infty} e_i(t) = 0$, $(i = 0, 1, 2)$, the system is synchronized. FIGURE 3 shows that the effect of the change of the coupling coefficient D is not obvious on $e(t)$. In order to

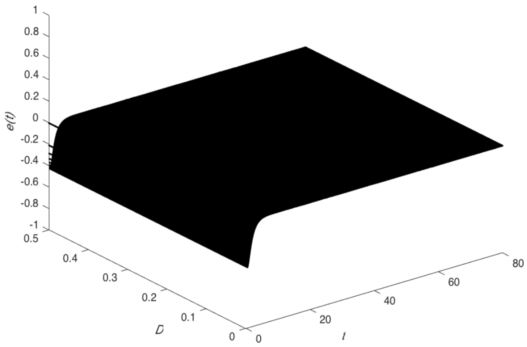

FIGURE 3. **Three-dimensional space diagram of error $e(t)$ changes with coupling coefficient D and time t.**

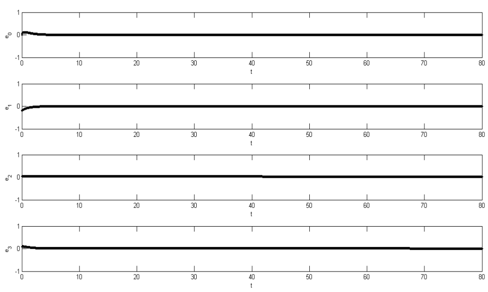

FIGURE 4. **The synchronization difference of the HR neuron model under the controller when $D = 0.2$.**

more clearly determine the changes of error $e(t)$ with time, we respectively select the coupling coefficient $D = 0.2$ and $D = 3.0$ and get the system synchronization difference shown in FIGURE 4. It is not difficult to see from FIGURE 4 that the synchronization difference gradually tends to zero and the system achieves synchronization status after the errors at the beginning. Therefore, the coupled HR neuron model can achieve system synchronization under the controller of equation (8).

IV. SECURE COMMUNICATION BASED ON COUPLED HR NEURON ADAPTIVE SYNCHRONIZATION

The main idea of applying chaos synchronization theory to information transmission is to use the pseudo-random characteristic of chaotic signals to hide the signals which need to be transmitted in the seemingly messy chaotic signals, and add the small input signals to the chaotic signals at the input end [24], [25]. Then the receiver uses a synchronous chaotic signal to demodulate useful information, so as to achieve the purpose of confidential information transmission. In 2002, Jiang ZP established a dual-channel chaotic secure information transmission system [26], which separates the transmission of information from synchronization, that is, the establishment of two channels at the sending and receiving ends at the same time: one is for the synchronization of the drive system and the response system, the other is used to transmit information. The schematic diagram of dual-channel chaotic confidential transmission system is shown in FIGURE 5.

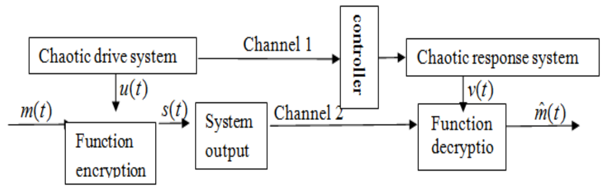

FIGURE 5. **Schematic diagram of dual channel chaotic security information system.**

In the diagram, $m(t)$ is the signal that needs to be transmitted, $u(t)$ is the signal transmitted by the drive system, $s(t)$ is the mixed signal in the channel, $\hat{m}(t)$ is the decrypted signal which is finally recovered, $v(t)$ is the chaotic response system output, then the synchronization difference between the decrypted signal and the original transmission signal is $e(t) = m(t) - \hat{m}(t)$. Through the state information of chaotic drive system and the designed encryption function, we can get mixed signal $s(t)$ from the information signal which needs to be transmitted through function encryption processing and the channel 2 transmission. The other channel 1 is used to transmit the chaotic drive system status information to the controller, and the chaotic response system of the controller ensures the synchronization of the two systems and then decrypts and recovers the received information of $\hat{m}(t)$ through the state information of the chaotic response system and the corresponding decryption function to complete the information transmission.

The chaotic signal synchronization technology is the core problem of the application of chaos synchronization theory to information transmission. According to the different application methods of chaotic analog signal, the synchronization technology has mainly three techniques: chaos modulation, chaos masking and chaotic keying. This article uses the chaotic masking technique. Chaos masking, also known as chaos concealment, is a technique proposed by Kocarev, Chua and Oppenheim et al. in the early 1990s which applies chaos theory to information transmission, and is mainly applied to the continuous information transmission systems [27]. The basic principle is that the signal to be transmitted is added to the chaotic signal generated by the chaotic system, so that the information is hidden or obscured in the chaotic signal, which can guarantee the security of information transmission. The signal transmitted in the channel is a chaotic signal, it has characteristics similar to noise, and is not easy to be found in the channel transmission. Even if it is found, it is difficult to extract information from the signal. And then complete the acceptance of the chaotic signal in the corresponding signal receiver, and use the function decryption method to separate the original signal to complete the safe information transmission. At present, in the chaotic masking technology, the concealment modes are mainly several kinds such as addition, multiplication or addition-multiplication and so on, this article chooses the addition processing.

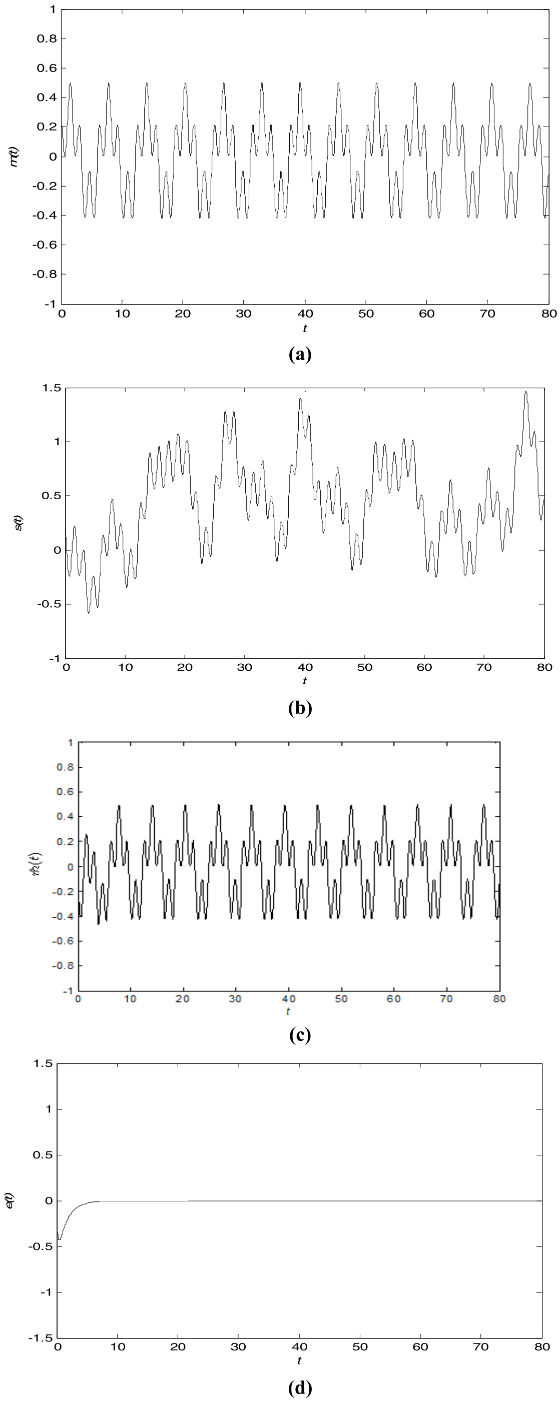

FIGURE 6. Simulation diagram of chaotic information transmission system when $D = 0.2$. (a) Signal that needs to be transmitted $m(t)$. (b) Mixed signal $s(t)$. (c) Decryption signal $\hat{m}(t)$. (d) Error of the original signal and the decryption signal.

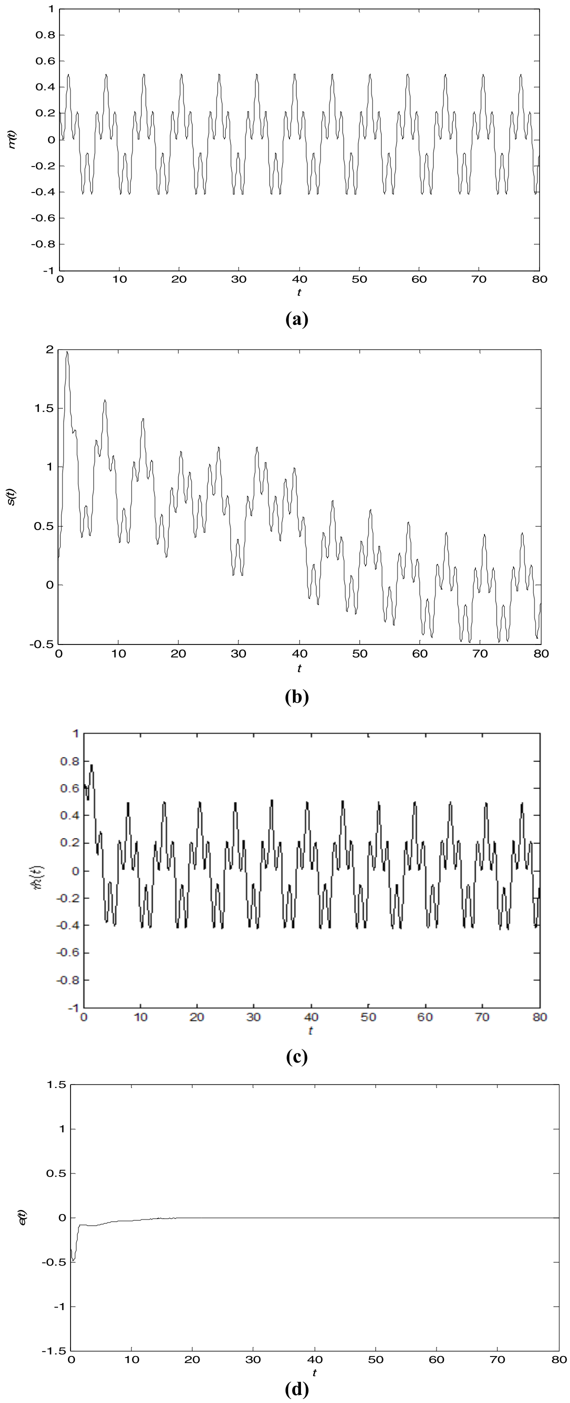

FIGURE 7. Simulation diagram of chaotic information transmission system when $D = 3.0$. (a) Signal that needs to be transmitted $m(t)$. (b) Mixed signal $s(t)$. (c) Decryption signal $\hat{m}(t)$. (d) Error of the original signal and the decryption signal.

Addition $s(t) = m(t) + u(t)$,
Multiplication $s(t) = m(t) \cdot u(t)$,
Addition-multiplication $s(t) = m(t) \cdot (1 + k \cdot u(t))$.

Chaotic masking technology is characterized by the fact that when the chaotic signal $s(t)$ is used in the chaotic response system, as long as the power of the transmission information signal $m(t)$ is smaller than the chaotic signal $s(t)$, the drive system and the response system can basically remain synchronized, and the information signal can be recovered approximately from the response system, i.e.

$$\hat{m}(t) = s(t) - v(t) = m(t) + u(t) - v(t)$$

It can be seen from FIGURE 6 and FIGURE 7 that the original signals which need to be transmitted change

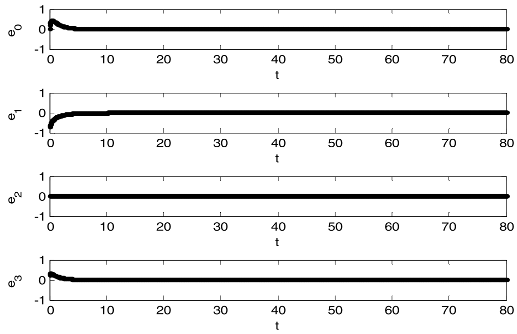

FIGURE 8. **Synchronization error diagram of the drive system and response system when $D = 0.2$.**

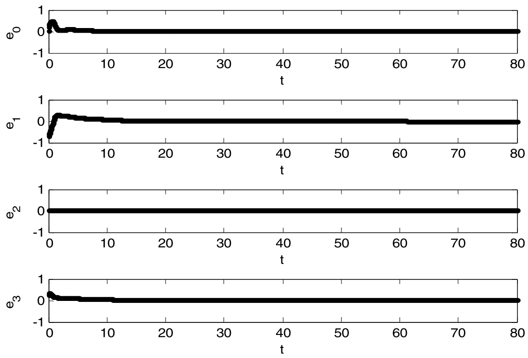

FIGURE 9. **Synchronization error diagram of the drive system and response system when $D = 3.0$.**

into mixed signals after chaotic encryption processing, and then the encryption processing of information is completed. After the receiving end receives the information transmitted through the encrypted channel, the function decrypts the decrypted signal. Then, the error between the decrypted signal and the original signal is calculated. As can be seen from FIGURE 6(d) and FIGURE 7(d), the error quickly tends to zero, indicating that after the chaotic encryption of the response system, the error between the decrypted information and the original information is very small, so it can be explained that the system can achieve a perfect encryption, and the confidential security is high.

Then, the synchronization difference between the drive system and the response system is obtained in this paper, as shown in FIGURE 8 and FIGURE 9 respectively, it can be seen from FIGURE 8 and FIGURE 9 that the synchronization difference between the two systems gradually tends to zero after a certain period of time at first and the two systems reach a synchronization status.

Since the drive system and the response system are basically synchronized, thus $u(t) - v(t) \approx 0$, so $\hat{m}(t) = m(t)$.

Choose coupling intensity $D = 0.2$ and $D = 3.0$ respectively, and keep other parameters unchanged, and then information signal sent is $m(t) = 0.3\sin(t) + 0.2\cos(4t)$, the relevant signal map of chaotic information transmission system can be obtained by Matlab numerical simulation, as shown in FIGURE 6 and FIGURE 7.

V. CONCLUSIONS

Based on the Lyapunov stability theorem, a nonlinear adaptive system is proposed to ensure the synchronization of two HR-coupled neuron systems for industrial internet of things. According to the different initial values of the neuron models, the system adjusts the value of the controller dynamically, which makes the system in better synchronization state and have good stability and adaptability. Besides, the realization method of the controller is also relatively simple and easy to implement in practical applications. Finally, this paper applies the controller to chaotic information transmission. The simulation results show that the controller can conduct encryption well and has high privacy and security, which is of certain practical significance to realize chaotic security communication.

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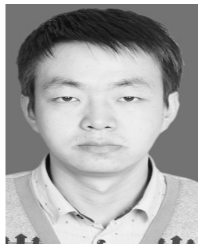
TIEJUN WANG received the doctor's degree from the Mathematics and Computer Science Institute, Northwest University for Nationalities, China, in 2017. She is currently an Associate Professor with the School of Mathematics and Computer Science Institute, Northwest University for Nationalities, China, in 2017. Her research interests include pattern recognition and computer network.



DICONG WANG received the bachelor's degree from Nanchang Hangkong University, China, in 2016. He is currently pursuing the master's degree with the School of Electronic Information Engineering, Lanzhou Jiaotong University, China. His research area is nonlinear dynamics of neurons.

KAIJUN WU received the master's and doctor's degrees from Lanzhou Jiaotong University, China, in 2009 and 2017, respectively. He is currently an Associate Professor with the School of Electronic and Information Engineering, Lanzhou Jiaotong University. His research interests include intelligent optimization algorithm and nonlinear dynamics of neurons.