Model-free Adaptive Control Design for Chaotic Systems Via Type-2 Recurrent Wavelet Fuzzy Brain Emotional Learning Networks

Xiaohua Zou (✉ zouxiaohua@czcit.edu.cn)

Changzhou College of Information Technology, Changzhou, China

Qingfeng Yang

Changzhou College of Information Technology, Changzhou, China

Feng He

Changzhou College of Information Technology, Changzhou, China

Mingsheng Ling

Changzhou College of Information Technology, Changzhou, China

Jianping Dai

Changzhou College of Information Technology, Changzhou, China

Research Article

Keywords: Type-2 recurrent wavelet fuzzy system, Sliding mode control, Brain Emotion Learning Network, Model-free adaptive control, Chaotic system

Posted Date: June 1st, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-560272/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Model-free adaptive control design for chaotic systems via Type-2 recurrent wavelet fuzzy Brain Emotional Learning Networks

Xiaohua Zou, Qingfeng Yang, Feng He, Mingsheng Ling, Jianping Dai

Changzhou College of Information Technology, Changzhou, China

Corresponding author: Xiaohua Zou (e-mail: zouxiaohua@ccit.edu.cn).

ABSTRACT: This paper introduces an optimal model named Self-Organizing Type-2 Recurrent Wavelet Fuzzy Brain Emotional Learning Network controller (SET2RWFBELNC) with self-evolving algorithm to gain optimal structure from zero initial rule, which merges Interval Type-2 Recurrent Wavelet Fuzzy System and Brain Emotional Learning Network (BELN). As an ideal controller, SET2RWFBELNC not only solves the problem of less information between master and slave systems, but also reduces the influence of external disturbance on synchronization of chaotic systems. Consequently, one model-free adaptive sliding mode controller based on SET2RWFBELNC, sliding model theory, and the asymptotic stability of the synchronization error is realized by robust compensation, in which the strong compensation used for the compensation of the network error. Besides, the Lyapunov function improves the stability of the model. Finally, simulation results of the chaotic system presented in this paper show the superiority of this method.

INDEX TERMS Type-2 recurrent wavelet fuzzy system, Sliding mode control, Brain Emotion Learning Network, Model-free adaptive control, Chaotic system.

I. INTRODUCTION

In recent years, neural network, fuzzy logic system, intelligent optimisation algorithm and other intelligent methods are more and more used in the research of chaos system identification and control. The Neural network is one of the most practical and classical methods in machine learning. The identification and control of chaotic system based on neural network has become the focus of many scholars. In reference[1], based on neural network and sliding mode control, a neural sliding mode controller is designed to realise the synchronization of uncertain chaotic system, which has fast response, good effect and strong robustness. In reference[2], the adaptive neural network is combined with sliding mode control, the synchronization of uncertain fractional order chaotic systems with different structures is realized, which is very consistent with the application of engineering. Fuzzy logic system has been proved to be a universal approximation and has been widely used in the research of chaotic system. In reference[3], a fuzzy adaptive synchronization control method is proposed, which is suitable for self-synchronization and different synchronization of chaos at the same time. In reference[4], proposed a kind of synchronous chaotic system with different structures. In reference[5], designed an adaptive synchronization controller, it solved the synchronization problem between unknown function and disturbance in chaotic system. In reference[6], proposed a chaotic system about TS model, it realized the fuzzy pulse control and synchronization. In

reference[7], proposed the fuzzy pulse control of chaotic dynamic systems.

These neural networks mentioned above have large computation and complexity. In order to solve this problem, brain emotional learning model is presented in [8,9], which has lower computation and complexity compared with the other neural networks, but the original BEL can't achieve desirable performance, so the fuzzy logic system introduced in the BEL model to improve the recognition accuracy. The second problem is that all the fuzzy logic systems in these papers are based on Type-1, which not handle the uncertainties more flexible. In order to solve this problem, we choose Type-2 as the better scheme, for which has been applied in various applications [10-12]. Furthermore, the reference[13,14] combined the Type-2 fuzzy logic set with the brain affective learning network, in which the author used this model to control robot. In reference[15], designed a wavelet fuzzy BELN, by which MIMO unconcern system can be controlled. In reference[16], proposed a Type-2 recurrent fuzzy BELN, As a new filter, active noise reduction can be realized.

According to the above analysis, this paper adopts an interval Type-2 recurrent wavelet fuzzy logic system combined with BELN to construct one model for emotion recognition. The main contributions of this paper including: 1) A new self-organizing Type-2 recursive wavelet fuzzy BELN is proposed. 2) Use the adaptive law to adjust the parameters online. 3) Using empty initial rules to automatically construct interval type two recursive wavelet

fuzzy BELN structure. 4) The validity of this method in emotion recognition is verified by numerical simulation.

II. GFORMULATION OF CHAOTIC SYSTEM SYNCHRONIZATION

Take the following unknown fractional-order chaotic system as the master-slave system:

$$C_t(x) = f(x, t) \quad (1)$$

$$C_t(y) = g(y, t) + bu + d$$

$x = [x_1, x_2, \dots, x_n]^T$, $y = [y_1, y_2, \dots, y_n]^T$ represent the state vector of the master and slave system, which are measurable. $f(x, t)$, $g(y, t)$ represent the unknown nonlinear functions. $u = (u_1, u_2, \dots, u_n)^T$ is the control input vector, $d = (d_1, d_2, \dots, d_n)^T$ denotes the external disturbance vector.

Then the synchronization error is designed as:

$$e = y - \lambda x - \eta$$

$$C_t e = g(y, t) - f(x, t) + bu + d$$

In the following part, one model-free adaptive controller is designed to ensure the error is to be zero.

III. METHODS

The SET2RWFBELN is composed as: the Amygdala Network for emotion judgment, the Orbitofrontal Cortex Network for emotion control. Interval Type-2 Recurrent Wavelet System is taken as the fuzzy inference part of SET2RWFBELN, then these two parts can be described as:

If x_1 is μ_{1j}^a and $\dots$ and x_i is μ_{ij}^a and $\dots$ and x_{n_i} is $\mu_{n_i j}^a$,

$$\text{Then } y_k^a = \omega_{jk} \quad (2)$$

If x_1 is μ_{1j}^o and $\dots$ and x_i is μ_{ij}^o and $\dots$ and x_{n_i} is $\mu_{n_i j}^o$,

$$\text{Then } y_k^o = v_{jk}$$

Where the membership functions grade and the weights for the two network could be described as: $\mu_{ij}^a = [\underline{\mu}_{ij}^a, \bar{\mu}_{ij}^a]$, $\mu_{ij}^o = [\underline{\mu}_{ij}^o, \bar{\mu}_{ij}^o]$ and $\omega_{jk} = [\underline{\omega}_{jk}, \bar{\omega}_{jk}]$, $v_{jk} = [\underline{v}_{jk}, \bar{v}_{jk}]$, respectively.

Structure of SET2RWFBELN

Fig.1 shows the SET2RWFBELN structure, which consists of the Amygdala Network and the orbitofrontal cortex network. It is divided into 6 layers: input layer, output layer, MF layer, weight memory layer, spatial firing layer, and summarily layer.

1). *Input layer*: The node of this input layer are $X = [x_1, x_2, \dots, x_{n_i}]^T$, where n_i is the number of the input signals. All the input raw data are transmitted directly to the next layer.

2). *MF layer*: The interval Type-2 Wavel membership function is the basis function, fuzzification is realized by Gaussian activation function. Then the approximation ability by using wavelet functions than triangle or Gaussian basis functions, so the learning speed could be increased. Furthermore, the recurrent term with previous information

is inserted in this layer, therefore, the performance of the network is further improved. The wavelet membership functions can be represented as:

$$\bar{\mu}_{ik} = \begin{cases} \left(\frac{(x_{ri} - c_{ik}^l)}{2\sigma_{ik}} \right) \exp \left(-\frac{(x_{ri} - c_{ik}^l)^2}{2\sigma_{ik}^2} \right) & x_{ri}(t) \leq c_{ik}^l \\ 1, & c_{ik}^l \leq x_{ri}(t) \leq c_{ik}^r \\ \left(\frac{(x_{ri} - c_{ik}^r)}{2\sigma_{ik}} \right) \exp \left(-\frac{(x_{ri} - c_{ik}^r)^2}{2\sigma_{ik}^2} \right) & x_{ri}(t) \geq c_{ik}^r \end{cases} \quad (3)$$

$$\underline{\mu}_{ik} = \begin{cases} \exp \left(-\frac{(x_{ri} - c_{ik}^r)}{2\sigma_{ik}} \right), & x_{ri}(t) \leq \frac{c_{ik}^l + c_{ik}^r}{2} \\ \exp \left(-\frac{(x_{ri} - c_{ik}^l)}{2\sigma_{ik}} \right), & x_{ri}(t) > \frac{c_{ik}^l + c_{ik}^r}{2} \end{cases}$$

Where the parameters c_{ik}^l , c_{ik}^r and σ_{ik} are the center and variance of the fuzzy rules of Type-2 wavelet membership functions. An interval MF $[\underline{\mu}_{ik}, \bar{\mu}_{ik}]$ represents the output of i th input feature and k th rule. $\tilde{x}_{ri} = [\underline{x}_{ri}, \bar{x}_{ri}]$ is the recurrent inputs, which could be given as:

$$\begin{aligned} \bar{x}_{ri} &= \bar{x}_i + r_i \bar{\mu}_{ik} (k-1) \\ \underline{x}_{ri} &= \underline{x}_i + r_i \underline{\mu}_{ik} (k-1) \end{aligned} \quad (4)$$

where r_i is the recurrent gain for the network.

3). *Spatial firing layer*: The upper and lower firing strengths in MFs and non-MFs constitute the rule of this layer. Calculate the firing intensity of Type-2 Fuzzy Rule according to Equation (5) below, which is an interval range.

$$\begin{aligned} F_k &= [\underline{f}_k, \bar{f}_k] \\ \underline{f}_k &= \prod_{i=1}^m \underline{\mu}_{ik}, k=1, 2, \dots, M \\ \bar{f}_k &= \prod_{i=1}^m \bar{\mu}_{ik} \end{aligned} \quad (5)$$

where F_k is the interval of the firing intensity of MFs, the m and M are number of input signals and fuzzy rules, respectively.

Fig.1 Structure of SET2RWFBELN

4). *Weight memory layer*: There are two memory spaces, Amygdala Memory(AM) and Orbitofrontal Memory(OM). Because firing space is an interval, so is the value of AM and OM. Therefore, the weight of the Amygdala Network at the k th output layer and the weight of the Orbitofrontal Network at the k th output layer can be obtained as followed.

$$\begin{aligned} \omega_k &= [\underline{\omega}_k, \bar{\omega}_k] \\ v_k &= [\underline{v}_k, \bar{v}_k] \end{aligned} \quad (6)$$

the updating rules of ω_k, v_k are introduced in the derivative form as:

$$\begin{aligned} \omega_k &= \beta[F_k \cdot (o_k - d_k)] \\ v_k &= \lambda[F_k \cdot (\max[0, d_k - a_k])] \end{aligned} \quad (7)$$

where β, λ indicate the learning rates of the updating rules, and o_k, a_k represent the outputs of the ω_k, v_k value.

5). *Defuzzification layer*: The output of the defuzzification layer can be calculated according to the output of firing space and power space. So we get the equation (8), y_k^a is the point value of Amygdala Network output, y_k^o is the point value of Orbitofrontal Network output.

$$\begin{aligned} y_k^a &= \frac{a_k^l + a_k^r}{2} = \frac{1}{2} \left(\frac{\sum_{j=1}^{n_j} (f_{jk} w_{jk})}{\sum_{j=1}^{n_j} f_{jk}} + \frac{\sum_{j=1}^{n_j} (\bar{f}_{jk} \bar{w}_{jk})}{\sum_{j=1}^{n_j} \bar{f}_{jk}} \right) \\ y_k^o &= \frac{o_k^l + o_k^r}{2} = \frac{1}{2} \left(\frac{\sum_{j=1}^{n_j} (f_{jk} v_{jk})}{\sum_{j=1}^{n_j} f_{jk}} + \frac{\sum_{j=1}^{n_j} (\bar{f}_{jk} \bar{v}_{jk})}{\sum_{j=1}^{n_j} \bar{f}_{jk}} \right) \end{aligned} \quad (8)$$

6). *Output layer*: The output of defuzzification space is an interval value, the output results of this layer can be calculated by using equation (8). As following:

$$y_{IT2RWFBELN} = y_k^a - y_k^o \quad (9)$$

Self-organizing of SET2RWFBELN

The optimal structure of SET2RWFBELN can be obtained by using the adaptive algorithm to determine the optimal rule. The number of rules must be appropriate, otherwise it will lead to long load times or failure to reflect all cases. Therefore, we need to choose the most moderate amount of data. Initially, there is no rules and MFs in the first space, when the first data entry, the first MFs is created. A self organizing algorithm is used to determine whether to create or delete rules and MFs. The fuzzy rules of RT2WFNN are expressed by membership function. In this paper, IT2FCM(Interval Type-2 Fuzzy C-Means) is used to choose the clustering center of this membership function. So the minimum objective function of IT2FCM is:

$$J_m(U, V) = \sum_{i=1}^c \sum_{k=1}^n \mu_{ik}(m) d_{ik}^2 \quad (10)$$

$$\begin{cases} \bar{\mu}_i(k) = \max \left(1 / \sum_{j=1}^c (d_{ik} / d_{jk})^{2/(m_1-1)}, \right. \\ \quad \left. 1 / \sum_{j=1}^c (d_{ik} / d_{jk})^{2/(m_2-1)} \right) \\ \underline{\mu}_i(k) = \min \left(1 / \sum_{j=1}^c (d_{ik} / d_{jk})^{2/(m_1-1)}, \right. \\ \quad \left. 1 / \sum_{j=1}^c (d_{ik} / d_{jk})^{2/(m_2-1)} \right) \end{cases} \quad (11)$$

where v_i is the cluster centers, x_k is input pattern, $d_{ik}^2 = \|x_k - v_i\|^2$ is the distance between these two.

The calculation steps of IT2FCM are as follows:

- 1) A Genetic algorithm is used to initialize the clustering center v , and setting the fuzzifiers and the value of c in the cluster prototypes.
- 2) Using the above equation (2) to calculate the upper and lower partitioning functions.
- 3) Calculating the distance $d_{ik}^2 = \|x_k - v_i\|^2$.
- 4) Interval Type-1 fuzzy sets $[c_L, c_R]$ are obtained by continuous iteration. Then using the optimal improved EKM algorithm to estimate both ends of interval fuzzy sets.
- 5) Updating the cluster center V' . V' is the new clustering center, so set $V = V'$.
- 6) Using $\mu_{ik} = (\mu_{ik}^L + \mu_{ik}^R) / 2$ to reduce Type-2 fuzzy partition matrix set.

T2FCM outputs an interval of Type-2 FS, which cannot be converted directly from Defuzzifier to Crisp Set. Therefore, we use type-reduction to achieve the transformation. Use type-reduction to find the centroid of the Type-2 Fuzzy Set(T2FS). Both Karnik–Mendel(KM) algorithm and Enhanced Karnik-Mendel(EKM) algorithm can effectively calculate the centroid of interval T2FS through continuous iteration. Here we used the EKM algorithm. It is improved by changing the initialization conditions of switch points and the searching method for switch points.

Robust controller

The optimal controller designed by SET2RWFBELN is used for approaching the ideal controller, which can be described as:

$$u^*(t) = u_{IT2RWFBELN}^*(w^*, v^*, \sigma^*, m^*, t) + \varepsilon(t) \quad (12)$$

The optimal parameters of can not be obtained, so we use the estimate controller $\hat{u}_{IT2RWFBELN}$ designed by SET2RWFBELN to estimate the optimal controller, which is described as:

$$\begin{aligned} u &= \hat{u}_{IT2RWFBELN}(\hat{w}, \hat{v}, \hat{\sigma}, \hat{m}, t) + u_r(t) \\ u_r(t) &= \hat{D}(t) \text{sgn}(s(t)) \\ \hat{D}(t) &= \eta_r |s(t)| \end{aligned} \quad (13)$$

Parameters learning algorithm of SET2RWFBELN

First, a high-order sliding mode is used:

$$\begin{aligned} s(t) &= e^{(n-1)} + (n-1)\lambda e^{(n-2)} + L + \lambda^{n-1}e \\ \hat{x}(t) &= e^{(n)} + K^T E \\ K &= [(n-1)\lambda, (n-2)\lambda^2, L, \lambda^{n-1}]^T \\ E &= [e^{(n-1)}, e^{(n-2)}, L, e^{(1)}] \end{aligned} \quad (14)$$

Define the Lyapunov cost function $V(s(t)) = (1/2)s^2(t)$, and get $\dot{V}(s(t)) = s(t)\dot{s}(t)$. Using the gradient descent method, the parameters of SET2RWFBELN are tuned online as shown below:

$$\begin{aligned} \hat{v}_{jk}(t+1) &= \hat{v}_{jk}(t) - \eta^v \frac{\partial s(t)}{\partial \hat{v}_{jk}} \\ \hat{v}_{jk}(t+1) &= \hat{v}_{jk}(t) - \eta^v \frac{\partial s(t)}{\partial \hat{v}_{jk}} \\ \hat{\omega}_{jk}(t+1) &= \hat{\omega}_{jk}(t) - \eta^\omega \frac{\partial s(t)}{\partial \hat{\omega}_{jk}} \\ \hat{\omega}_{jk}(t+1) &= \hat{\omega}_{jk}(t) - \eta^\omega \frac{\partial s(t)}{\partial \hat{\omega}_{jk}} \\ \hat{c}_{jk}^a(t+1) &= \hat{c}_{jk}^a(t) - \eta_c^a \frac{\partial s(t)}{\partial \hat{c}_{jk}^a} \\ \hat{c}_{jk}^a(t+1) &= \hat{c}_{jk}^a(t) - \eta_c^a \frac{\partial s(t)}{\partial \hat{c}_{jk}^a} \\ \hat{c}_{jk}^o(t+1) &= \hat{c}_{jk}^o(t) - \eta_c^o \frac{\partial s(t)}{\partial \hat{c}_{jk}^o} \\ \hat{c}_{jk}^o(t+1) &= \hat{c}_{jk}^o(t) - \eta_c^o \frac{\partial s(t)}{\partial \hat{c}_{jk}^o} \\ \hat{\sigma}_{jk}^a(t+1) &= \hat{\sigma}_{jk}^a(t) - \eta_\sigma^a \frac{\partial s(t)}{\partial \hat{\sigma}_{jk}^a} \\ \hat{\sigma}_{jk}^o(t+1) &= \hat{\sigma}_{jk}^o(t) - \eta_\sigma^o \frac{\partial s(t)}{\partial \hat{\sigma}_{jk}^o} \end{aligned}$$

Where η^ω is the learning rate of weight updates of the Orbitofrontal cortex, η^v is the learning rate of weight updates of Amygdala Network. $\eta_c^a, \eta_\sigma^a, \eta_c^o, \eta_\sigma^o$ represent the learning rate of mean and variance of Type-2 Wavelet MFs respectively. η_r^a, η_r^o represent the learning rates for updating the IF-indices indicate the hesitation level of recurrent.

Using the chain rule to derive the above terms, the following results can be obtained:

$$\begin{aligned} \frac{\partial s(k)}{\partial \hat{\omega}_{jk}} &= \frac{\partial s}{\partial \hat{y}_{IT2RWFBELN}} \frac{\partial \hat{y}_{IT2RWFBELN}}{\partial y_k^a} \frac{\partial y_k^a}{\partial a_k^l} \frac{\partial a_k^l}{\partial \hat{\omega}_{jk}} \\ &= \frac{1}{2} e(t) \frac{f_{jk}^a}{\sum_{j=1}^{n_j} f_{jk}^a} \\ \frac{\partial s(k)}{\partial \hat{\omega}_{jk}} &= \frac{\partial s}{\partial \hat{y}_{IT2RWFBELN}} \frac{\partial \hat{y}_{IT2RWFBELN}}{\partial y_k^a} \frac{\partial y_k^a}{\partial a_k^l} \frac{\partial a_k^l}{\partial \hat{\omega}_{jk}} \\ &= \frac{1}{2} e(t) \frac{\bar{f}_{jk}^a}{\sum_{j=1}^{n_j} \bar{f}_{jk}^a} \\ \frac{\partial s(k)}{\partial \hat{v}_{jk}} &= \frac{\partial s}{\partial \hat{y}_{IT2RWFBELN}} \frac{\partial \hat{y}_{IT2RWFBELN}}{\partial y_k^o} \frac{\partial y_k^o}{\partial o_k^l} \frac{\partial o_k^l}{\partial \hat{v}_{jk}} \\ &= \frac{1}{2} e(t) \frac{f_{jk}^o}{\sum_{j=1}^{n_j} f_{jk}^o} \\ \frac{\partial s(k)}{\partial \hat{v}_{jk}} &= \frac{\partial s}{\partial \hat{y}_{IT2RWFBELN}} \frac{\partial \hat{y}_{IT2RWFBELN}}{\partial y_k^o} \frac{\partial y_k^o}{\partial o_k^r} \frac{\partial o_k^r}{\partial \hat{v}_{jk}} \\ &= \frac{1}{2} e(t) \frac{\bar{f}_{jk}^o}{\sum_{j=1}^{n_j} \bar{f}_{jk}^o} \\ \frac{\partial s(k)}{\partial \hat{\sigma}_{ij}^a} &= \sum_{k=1}^{n_k} \left(\frac{\partial s(k)}{\partial \hat{y}_{IT2RWFBELN}} \frac{\partial \hat{y}_{IT2RWFBELN}}{\partial y_k^a} \left(\frac{\partial y_k^a}{\partial a_k^l} \frac{\partial a_k^l}{\partial f_{jk}^a} \frac{\partial f_{jk}^a}{\partial \hat{\sigma}_{ij}^a} + \frac{\partial y_k^a}{\partial a_k^r} \frac{\partial a_k^r}{\partial \bar{f}_{jk}^a} \frac{\partial \bar{f}_{jk}^a}{\partial \hat{\sigma}_{ij}^a} \right) \right) \\ &= \frac{1}{2} e(t) \sum_{k=1}^{n_k} \left(\frac{\omega_{jk} - a_k^l}{\sum_{j=1}^{n_j} f_{jk}^a} \frac{\partial f_{jk}^a}{\partial \hat{\sigma}_{ij}^a} + \frac{\bar{\omega}_{jk} - a_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}^a} \frac{\partial \bar{f}_{jk}^a}{\partial \hat{\sigma}_{ij}^a} \right) \\ \frac{\partial s(k)}{\partial \hat{\sigma}_{ij}^o} &= \sum_{k=1}^{n_k} \left(\frac{\partial s(k)}{\partial \hat{y}_{IT2RWFBELN}} \frac{\partial \hat{y}_{IT2RWFBELN}}{\partial y_k^o} \left(\frac{\partial y_k^o}{\partial o_k^l} \frac{\partial o_k^l}{\partial f_{jk}^o} \frac{\partial f_{jk}^o}{\partial \hat{\sigma}_{ij}^o} + \frac{\partial y_k^o}{\partial o_k^r} \frac{\partial o_k^r}{\partial \bar{f}_{jk}^o} \frac{\partial \bar{f}_{jk}^o}{\partial \hat{\sigma}_{ij}^o} \right) \right) \\ &= \frac{1}{2} e(t) \sum_{k=1}^{n_k} \left(\frac{v_{jk} - o_k^l}{\sum_{j=1}^{n_j} f_{jk}^o} \frac{\partial f_{jk}^o}{\partial \hat{\sigma}_{ij}^o} + \frac{\bar{v}_{jk} - o_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}^o} \frac{\partial \bar{f}_{jk}^o}{\partial \hat{\sigma}_{ij}^o} \right) \\ \frac{\partial s(k)}{\partial \hat{c}_{ij}^a} &= \frac{1}{2} e(t) \sum_{k=1}^{n_k} \left(\frac{\omega_{jk} - a_k^l}{\sum_{j=1}^{n_j} f_{jk}^a} \frac{\partial f_{jk}^a}{\partial \hat{c}_{ij}^a} + \frac{\bar{\omega}_{jk} - a_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}^a} \frac{\partial \bar{f}_{jk}^a}{\partial \hat{c}_{ij}^a} \right) \\ \frac{\partial s(k)}{\partial \hat{c}_{ij}^o} &= \frac{1}{2} e(t) \sum_{k=1}^{n_k} \left(\frac{\omega_{jk} - a_k^l}{\sum_{j=1}^{n_j} f_{jk}^o} \frac{\partial f_{jk}^o}{\partial \hat{c}_{ij}^o} + \frac{\bar{\omega}_{jk} - a_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}^o} \frac{\partial \bar{f}_{jk}^o}{\partial \hat{c}_{ij}^o} \right) \\ \frac{\partial s(k)}{\partial \hat{c}_{ij}^a} &= \frac{1}{2} e(t) \sum_{k=1}^{n_k} \left(\frac{v_{jk} - o_k^l}{\sum_{j=1}^{n_j} f_{jk}^a} \frac{\partial f_{jk}^a}{\partial \hat{c}_{ij}^a} + \frac{\bar{v}_{jk} - o_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}^a} \frac{\partial \bar{f}_{jk}^a}{\partial \hat{c}_{ij}^a} \right) \\ \frac{\partial s(k)}{\partial \hat{c}_{ij}^o} &= \frac{1}{2} e(t) \sum_{k=1}^{n_k} \left(\frac{v_{jk} - o_k^l}{\sum_{j=1}^{n_j} f_{jk}^o} \frac{\partial f_{jk}^o}{\partial \hat{c}_{ij}^o} + \frac{\bar{v}_{jk} - o_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}^o} \frac{\partial \bar{f}_{jk}^o}{\partial \hat{c}_{ij}^o} \right) \end{aligned}$$

V. SIMULATIONS

Numerical results of the chaotic systems have been done in this part to show the effectiveness of the model-free adaptive controller. The Lorenz, Lu and Chen chaotic systems are simulated respectively, and the following four control strategies are compared and analyzed in this part, which includes PSO-SET2FBELC[17], AWC MAC[18],

T2FBELC and the proposed method in this paper. The initial position is chosen as: $x(t)=[1.5,2.0,1.0]$, $y(t)=[1.0,1.6,0.5]$. The disturbances are chosen as: $d(t)=[0.2\cos(\pi),0.1\cos(t),0.3\cos(2t)]$; The control vectors are $u(t)=[u_1(t),u_2(t),u_3(t)]$; The system uncertainties are chosen as: $\Delta f(y)=rand(\cdot)[0.2y_1,0.2y_2,0.2y_3]$; The system tracking errors are depicted as: $e(t)=[e_1(t),e_2(t),e_3(t)]$. The performance of the control system is evaluated by Root Mean Square Error (RMSE)[17], which is also used here for evaluating the performance of different controllers:

$$RMSE = \sqrt{\frac{1}{n_h} \sum_{h=1}^{n_h} ((e_{1h})^2 + (e_{2h})^2 + (e_{3h})^2)} \quad (15)$$

Lorenz chaotic system

Using the proposed method, we simulate the Lorenz chaotic system, and the results are shown in Fig. 2, which shows the tracking errors, we can see that the proposed method performs better than the other methods.

Fig.2 Tracking error of Lorenz chaotic system

Lu chaotic system

Fig. 3 shows the simulation comparison between Lu chaotic system and our proposed method, which shows the tracking errors. Simulation results show that our method has better performance than other methods.

Fig.3 Tracking errors for Lu chaotic system

Chen chaotic system

Fig.4 is a simulation comparison between Chen chaotic system and our method, which shows the tracking errors. From the results, we can see that the proposed method could achieve smaller errors than the other methods.

Fig.4 Tracking errors for Chen chaotic system

Table.1 Computation time and RMSE for comparison

	Time	RMSE1	RMSE2	RMSE3
T2FBELC	0.0162	0.0854	0.08	0.08
AWCMAC[18]	0.0153	0.0926	0.0913	0.0917
SET2RWFBELC	0.0173	0.0805	0.0784	0.0809
PSOSET2FBELC	0.0184	0.0808	0.0796	0.0814

In order to verify the performance of the proposed control method, the computation time and RMSEs have been listed in the Table.1. All of data used here are just from the above three cases under 10 times running. From the comparison, we can conclude that the controller proposed in this paper can not only realize the synchronization of master and slave systems, but also has shorter time and smaller tracking error.

VII. CONCLUSION

This paper constructs Type-2 recurrent wavelet fuzzy Brain Emotional Learning Network (SET2RWFBELN), and which is used to synchronize unknown nonlinear chaotic systems with external disturbances. The SET2RWFBELN takes advantages of dealing with uncertainties by Interval Type-2 Recurrent Wavelet Fuzzy System and the lower computation by BELN. Finally, some comparison results show that proposed control method could handle the system uncertainties and external disturbances with smaller errors for synchronization of the chaotic systems. Our future task will focus on reducing the time consumption. With the advent of the information age, data information is becoming more and more large, and more and more complex. We believe that this self-organizing Type-2 method has great application space.

DATA AVAILABILITY

All data analyzed during this study are from the published references.

REFERENCES

- [1] Q. H. Li, X. F. Liao, H.Y. Huang. Synchronization of uncertain chaotic systems based on neural network and sliding mode control, *Acta Physica Sinica*, 2011, 60(2): 205-212
- [2] Y.A. Zhang, M.Z. Yu, H. L. Wu. Sliding mode synchronization of fractional-order chaotic systems based on adaptive neural network. *Control and Decision*. 2015, 30(5): 882-886.
- [3] D.Yue, Jun Yoneyama. Adaptive fuzzy synchronization of chaotic systems with uncertainties. *Acta Physica Sinica*, 2003, 52(2): 292-297
- [4] D.S. Zhang, H.G.Zhang, A. P. Li. Generalized synchronization of two non-identical chaotic systems based on fuzzy model. *Acta Physica Sinica*, 2007, 56(6): 3121-3126.
- [5] Y. H. Wang, Z.L.Gao, Q. R. Wang, Y. Zhang,. Synchronization control for a class of chaotic systems based on adaptive fuzzy logic systems. *Control and Decision*, 2013, 28(9): 1309-1314.
- [6] C. Hu, Jiang H J, Teng Z D. Fuzzy impulsive control and synchronization of general chaotic system. *Acta Applicandae Mathematica*, 2010, 109(2): 463-485.
- [7] Y. Liu, S. W. Zhao, T-S model-based impulsive control for chaotic systems and its application. *Mathematics and Computers in Simulation*, 2011, 81(11): 2507-2516
- [8] J. Moren, A. Balkenius, A computational model of emotional learning in the amygdala, in: *Proceedings of the 6th International Conference on the Simulation of Adaptive Behaviour*, 2000: 115-124.
- [9] J.E. LeDoux, Emotion and the limbic system concept, *Concept. Neurosci.* 2 (1991) 169-199.
- [10] X. J. Chen, D. Li, X. Wang, X. B. Yang. "Rough intuitionistic Type-2 fuzzy c-means clustering algorithm for MR image segmentation. *IET Image Processing*", 2019, 13(4): 607-614.
- [11] X. J. Chen, D. Li, X. Wang, X. B. Yang, A Deep Convolutional Neural Network With Fuzzy Rough Sets for FER. *IEEE Access* 2020, 8: 2772-2779.
- [12] Xiangjian Chen, Di Li, Xun Wang, Xibei Yang, Hongmei Li, Rough intuitionistic Type-2 fuzzy c-means clustering algorithm for MR image segmentation. *IET Image Processing*, 2019, 13(4): 607-614
- [13] Le T-L, Lin C-M, Huynh T-T, Self-evolving Type-2 fuzzy brain emotional learning control design for chaotic systems using PSO, *Applied Soft Computing Journal*, 2018, 73: 418-433.
- [14] Chao, F, Zhou. D. J, Lin. C. M, Type-2 Fuzzy Hybrid Controller Network for Robotic Systems. *IEEE Transactions on Cybernetics*. 2019, 1-15: 2168-2267.
- [15] J. Zhao, Chih. M. L, and F. Chao, Wavelet Fuzzy Brain Emotional Learning Control System Design for MIMO Uncertain Nonlinear Systems, *Frontiers in neuroscience*, 2019, 12: 917-931.
- [16] L. L. Le, T. T. Huynh, C. M. Lin, Adaptive filter design for active noise cancellation using recurrent Type-2 fuzzy brain emotional learning neural network, *Neural Computing and Applications*, 2019, <https://doi.org/10.1007/s00521-019-04366-8>.
- [17] T. L. Le, C. M. Lin, T. T. Huynh. Self-evolving Type-2 fuzzy brain emotional learning control design for chaotic systems using PSO. *Applied Soft Computing Journal*. 2018, 73: 418-433
- [18] C. M. Lin, M. H. Lin, R. G. Yeh, Synchronization of unified chaotic system via adaptive wavelet cerebellar model articulation controller, *Neural Comput. Appl.* 2013, 23 (3-4): 965-973.

ACKNOWLEDGEMENTS

This paper is the research results of the Provincial Engineering Research Center of Jiangsu (the Innovation and Application of Jiangsu Small Business Industrial Internet Engineering Research Center), and the Jiangsu Higher Education Philosophy and Social Science Excellent Innovation Team (Jiangsu Digital Creative Industry High-quality Technical and Skilled Talents Development Research Team).

This research work was supported by Natural Science Research Project for Higher Education of Jiangsu (18KJB480001), Jiangsu Cyan Engineering in Young academic leaders 2019, Natural Science Research Project of CCIT (CXZK201805Q), Open Lab of Edge of Computing for Smart Manufacturing of CCIT (KYPT201802z), Changzhou Key Laboratory of High Technology (CM20183004), Laboratory of Application and Research of Artificial Intelligence Technology (PYPT201805Z).

AUTHOR CONTRIBUTION STATEMENT

Qingfeng Yang and Xiaohua Zou designed experiments; Feng He and Xiaohua Zou carried out experiments;

Mingsheng Ling analyzed experimental results. Jianping Dai analyzed sequencing data and developed Xiaohua Zou wrote the manuscript.

ADDITIONAL INFORMATION

With no Competing Interests

FIGURE LEGEND

Fig.1 Structure of SET2RWFBELN

Fig.2 Tracking error of Lorenz chaotic system

Fig.3 Tracking errors for Lu chaotic system

Fig.4 Tracking errors for Chen chaotic system

TABLES

Table.1 Computation time and RMSE for comparison

Figures

Figure 1

Structure of SET2RWFBELN

Figure 2

Tracking error of Lorenz chaotic system

Figure 3

Tracking errors for Lu chaotic system

Figure 4

Tracking errors for Chen chaotic system