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

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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 sloved 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. FORMULATION OF CHAOTIC SYSTEM SYNCHRONIZATION

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

\[ C_1'(x) = f(x, t) \]
\[ C_2'(y) = g(y, t) + bu + d \]

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

Then the synchronization error is designed as:

\[ e = y - \lambda x - \eta \]
\[ C_e = g(y, t) - f(x, t) + bu + d \]

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 the SET2RWFBELN, then these two parts can be described as:

1. MF layer: The node of this input layer are \( \mu_{x} = \mu_{x}^{l} , \cdots , \mu_{x}^{u} \) and \( \mu_{x}^{l} = \mu_{x}^{l} \), then \( \mu_{x}^{u} = \mu_{x}^{u} \).

2. 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.

\[ F_i = f_1, \cdots, f_M \]
\[ f_i = \prod_{i=1}^{M} [d_{l}, d_{r}] \]
\[ F_i = \prod_{i=1}^{M} [d_{l}, d_{r}] \]

where \( F_i \) is the interval of the firing intensity of MFs, the \( m \) and \( M \) are number of input signals and fuzzy rules, respectively.
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 4th output layer and the weight of the Orbitofrontal Network at the kth output layer can be obtained as followed.

\[ \omega_k = [\omega_k^a, \omega_k^o] \]
\[ \nu_k = [\nu_k^a, \nu_k^o] \]

the updating rules of \( \omega_k, \nu_k \) are introduced in the derivative form as:

\[ \omega_k = \beta [F_i - (\omega_k - d_k)] \]
\[ \nu_k = \lambda [F_i - (\max[0, d_k - a_k])] \]

where \( \beta, \lambda \) indicate the learning rates of the updating rules, and \( \omega_k, a_k \) represent the outputs of the \( \omega_k, \nu_k \) 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.

\[ y_k^a = \frac{a_k^l + a_k^u}{2} = \frac{1}{2} \left( \sum_{j=1}^{n} \left( \frac{f_{jk} \cdot \nu_j^a}{\sum_{i=1}^{m} f_{ik}} \right) + \sum_{j=1}^{n} \left( \frac{\nu_j^a \cdot \mu_j^a}{\sum_{i=1}^{m} \mu_j} \right) \right) \]
\[ y_k^o = \frac{a_k^l + a_k^u}{2} = \frac{1}{2} \left( \sum_{j=1}^{n} \left( \frac{f_{jk} \cdot \nu_j^o}{\sum_{i=1}^{m} f_{ik}} \right) + \sum_{j=1}^{n} \left( \frac{\nu_j^o \cdot \mu_j^o}{\sum_{i=1}^{m} \mu_j} \right) \right) \]

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

\[ y_{IT2RFBFELN} = y_k^a - y_k^o \]

Self-organizing of SET2RFBFELN

The optimal structure of SET2RFBFELN 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:

\[
J_{\mu}(U, V) = \sum_{i=1}^{m} \sum_{j=1}^{n} \mu_{jk}(m) d_{jk}^2
\]

\[
\mu_{jk}(m) = \max \{ \sum_{i=1}^{m} d_{ik} / d_{jk} \} \]
\[
\mu_{jk}(m) = \min \{ \sum_{i=1}^{m} d_{ik} / d_{jk} \} \]

where \( v_k \) is the cluster point value, \( x_k \) is input pattern, \( d_{jk} = \| x_k - v_k \| \) 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 \( d_{jk} = \| x_k - v_k \| \).
4) Interval Type-1 fuzzy sets \([c_l, c_u]\) 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 \( \mu_k = (\mu_k^l + \mu_k^u) / 2 \) 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:
\[ u'(t) = u_{IT2RWFBELN}(w', v', \sigma', m', t) + e(t) \]
(12)
The optimal parameters of \( e \) 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:
\[ u = \hat{u}_{IT2RWFBELN}(\hat{w}, \hat{v}, \hat{\sigma}, \hat{m}, t) + u_i(t) \]
\[ \hat{D}(t) = \eta_i | s(t) | \]
(13)

Parameters learning algorithm of SET2RWFBELN
First, a high-order sliding mode is used:
\[ s(t) = e^{(n-1)} + (n-1)\lambda e^{(n-2)} + L + \lambda^{(n-2)}e \]
\[ \lambda = ((n-2)\lambda, e^{(n-2)} + L, \lambda^{(n-2)}) \]
\[ E = [e^{(n-2)}, e^{(n-1)}, L, e^{(n-1)}] \]

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

Using the chain rule to derive the above terms, the following results can be obtained:
\[ \frac{\dot{e}(k)}{\dot{\sigma}^o} = \frac{\dot{e}_s}{\dot{\sigma}^o_{IT2RWFBELN}} \]
\[ \frac{\dot{e}(k)}{\dot{u}^o} = \frac{\dot{e}_s}{\dot{u}^o_{IT2RWFBELN}} \]
\[ \frac{\dot{e}(k)}{\dot{v}^o} = \frac{\dot{e}_s}{\dot{v}^o_{IT2RWFBELN}} \]
\[ \frac{\dot{e}(k)}{\dot{w}^o} = \frac{\dot{e}_s}{\dot{w}^o_{IT2RWFBELN}} \]

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], AWCMAC[18],
T2FBELC and the proposed method in this paper. The initial position is chosen as: 
$$x(t) = [1.5, 2, 0, 1, 0], \quad y(t) = [1.0, 1, 6, 0, 5].$$  

The disturbances are chosen as: 
$$d(t) = [0.2\cos(\pi t), 0.1\cos(t), 0.3\cos(2t)].$$  

The control vectors are chosen as: 
$$u(t) = [u_1(t), u_2(t), u_3(t)].$$  

The system uncertainties are chosen as: 
$$f_1(t) = 2.0, f_2(t) = 2.0, f_3(t) = 2.0.$$  

The control errors are depicted as: 
$$e(t) = [e_1(t), e_2(t), e_3(t)].$$  

The performance of the control system is evaluated by the Root Mean Square Error (RMSE)

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

**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.

**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.

**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.

**Table.1 Computation time and RMSE for comparison**

| Method          | 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.

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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 INFOTMATION
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
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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