INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 16, Issue: 4, Month: August, Year: 2021
Article Number: 4215, https://doi.org/10.15837/ijccc.2021.4.4215

CCC Publications

# Finite Time Synchronization of Inertial Memristive Neural Networks with Time Varying Delay

Y.J. Pang, S.M. Dong

**Yajing Pang***
Hebei University of Science and Technology
Shijiazhuang 050000, China
*Corresponding author: pangyj2020@163.com

**Shengmei Dong**
Shijiazhuang Nanyangzhuang Primary School
Shijiazhuang 050000, China
dsm3012431882@163.com

**Abstract**

Finite time synchronization control of inertial memristor-based neural networks with varying delay is considered. In view of drive and response concept, the sufficient conditions to ensure finite time synchronization issue of inertial memristive neural networks is given. Based on Lyapunov finite time asymptotic theory, a kind of feedback controllers is designed for inertial memristor-based neural networks to realize the finite time synchronization. Based on Lyapunov stability theory, close loop error system can be proved finite time and fixed time stable. Finally, illustrative example is given to illustrate the effectiveness of theoretical results.

**Keywords:** finite time, neural networks, synchronization.

## 1 Introduction

At present, the dynamic systems appearing in the fields of engineering applications and natural sciences are becoming more and more complex, and control purposes are also diversified. In this case, it is inevitable that control theory needs to provide more effective control methods and strategies. In the actual industrial production and manufacturing, the control precision of the equipment is continuously improved. At the same time, industrial production often requires multiple devices to achieve synchronization effects in terms of time, position, and speed, which requires reasonable coordination between events that occur in the system. Synchronization in the system can also be called timely or synchronized.

The phenomenon in which two phases are in harmony is called chaotic synchronization, which is actually a common phenomenon in nature. In the 1990s, Peroca and Carroll proposed a chaos control method (P-C), and first observed chaotic synchronization in electronic circuits. In fact, the phenomenon that several coupling units achieve synchronization through coordination not only occurs widely in nature, but also common in actual production applications, and is very important and has to be researched, so synchronization control has always been a hot topic in the academic engineering field.

As we all know, neuron is the basic unit of neural network function realization, with complex nonlinear properties, such as chaos, periodicity and bifurcation. The composition of a neural network includes a large number of neuron structures. A single neuron cannot realize the processing and processing of complex information, and it requires the coupling of many neuron clusters to complete it. Synchronization is a manifestation of neuron coupling, so the study of neuron synchronization is particularly important.

Nowadays, with the continuous emergence of control problems and practical needs in the actual engineering field, the research on synchronization stability in the academic engineering field is becoming more and more popular, and a large number of research results and research directions have also been produced, such as brain network synchronization, complex networks Synchronization, transient synchronization, global synchronization, etc., and scholars have studied synchronization problems under complex conditions. Even though there have been a lot of results in the field of synchronization, there are still a lot of problems to be studied and solved in the world of nonlinear systems.

Chaos, as a very interesting nonlinear phenomenon, has been intensively investigated in many fields of science and technology over the last four decades. Recently, chaos synchronization has attracted increasing attention from various communities due to its powerfully potential applications in laser physics, chemical reactor, secure communication, biomedical and so on [10, 21]. Many methods have been proposed to achieve chaos control and synchronization, such as the passive control method, backstepping design method, impulsive control method, adaptive control method, sliding mode control, control Lyapunov function (CLF) method and nonlinear feedback method, etc. The controllers derived from the above methods are nonlinear. In a real industry process, because the linear feedback controllers are economic and easy to implement, they possess a high value in applications [1, 4].

Since the first publication of chaotic synchronization by Pecora in naval Laboratory in 1990 [12], the synchronization problem has attracted wide attention from scholars due to the widespread existence of complex chaotic phenomena in nature and engineering systems [7]. The synchronization theory has been reflected and applied in both nature and engineering circles, such as laser network synchronization [22], resonance synchronization [18] and epilepsy [15]. In order to solve this complex nonlinear chaotic behavior and completely reconstruct the chaotic states of the two systems, scholars have proposed many synchronization strategies, such as generalized synchronization [6], complete synchronization [23], coupled synchronization [9], etc.

As is known to all, neural network has attracted much attention in the field of academic engineering for its unique characteristics. With the in-depth study of neural network and the development of synchronization theory, network system synchronization has attracted extensive attention from scholars in recent years. In Chu's study [2], two consistent fractal-order differential inequalities are established to deal with the global exponential quasi-synchronization of a consistent FCDN, and the global exponential quasi-synchronization of a conformal fractal-order complex dynamic network (FCDN) is realized by periodic and intermittent pinning control. Gan et al. [5] believed that a controller based on Markov scheduling protocol was designed to solve the mean-square inverse synchronization problem of periodic BAM neural network (NN) with time-varying delay. The theory of differential inclusion is combined with the definition of Filippov solution, and the interval parameter system is established to study the exponential synchronization of CVMDNN based on complex valued memristor [11]. And in related study, sufficient conditions for finite time synchronization bounds are derived according to Markov observations, thus verifying the finite time synchronization of coupled neural networks with hopping internal coupling and non-fragile controllers [8]. Cui et al. [3] considered that the fixed-time synchronization of Markov jumping fuzzy neural networks with random disturbance and leakage time-varying delays was studied by designing time-dependent controllers with or without fuzzy terms.

According to the existing results, several control strategies can be given to realize the synchronization strategy mentioned above. For example, sliding mode control [17], Backstepping control [19], adaptive control ![13] and active control [20], etc. The above control strategies obviously have their own advantages in different situations. Among them, there is a kind of linear feedback control [14] with extremely superior effect for chaotic system synchronization and differential synchronization, and chaotic system synchronization has extremely high value in some practical applications [16].

The rest of this brief is organized as follows. The considered model and some necessary assumptions are given in Section 2, Section 3 presents finite time and fixed time synchronization criteria and rigorous mathematical proof. Section 4 given the numerical simulation and conclusion is given in Section 5.

## 2 Preliminaries

The inertial memristor-based neural networks model:

$$\begin{array}{l} \ddot{x}_i(t) = -a_i\dot{x}_i(t) - b_ix_i(t) + c_{ij}(x_i(t))f_j(x_j(t)) + d_{ij}(x_i(t))f_j(x_j(t-\tau(t))) + I_i(t) \\ i = 1, 2, \dots, n \end{array} \tag{1}$$

where $x_i(t)$ represents the state of the i-th neuron; $a_i > 0, b_i > 0$ are constants, $f_i()$ is activation function, $\tau(t)$ is varying delay, which satisfies $0 \le \tau(t) \le \tau$, $I_i(t)$ is external input, $c_{ij}(x_i(t)), d_{ij}(x_i(t))$ are memristive connection weights, which are given by

$$\begin{array}{l} c_{ij}(x) = \begin{cases} c'_{ij}, |x| \le T_i \\ c''_{ij}, |x| > T_i \end{cases} \\ d_{ij}(x) = \begin{cases} d'_{ij}, |x| \le T_i \\ d''_{ij}, |x| > T_i \end{cases} \quad i, j = 1, 2, \dots n \end{array} \tag{2}$$

where $c'_{ij}, c"_{ij}, d'_{ij}, d"_{ij}$ and $T_i$ are known constants.

By introducing the following variable substitution $x_{1i}, x_{2i}$ as

$$x_{1i} = x_i x_{2i} = \dot{x}_i \tag{3}$$

Then, the system can be rewritten as

$$\begin{cases} \dot{x}_{1i} = x_{2i} \\ \dot{x}_{2i} = -a_ix_{2i}(t) - b_ix_{1i}(t) + c_{ij}(x_{1i}(t))f_j(x_{1j}(t)) \\ \quad +d_{ij}(x_{1i}(t))f_j(x_{1j}(t-\tau(t))) + I_i(t) \end{cases} \tag{4}$$

This is referred to as drive system, and the response system can be described by

$$\ddot{y}_i(t) = -a_i\dot{y}_i(t) - b_iy_i(t) + c_{ij}(y_i(t))f_j(y_j(t)) + d_{ij}(y_i(t))f_j(y_j(t-\tau(t))) + I_i(t) \tag{5}$$

Similarly, by introducing variable substitution

$$\begin{cases} \dot{y}_{1i}(t) = y_{2i}(t) + u_{1i}(t) \\ \dot{y}_{2i}(t) = -a_iy_{2i}(t) - b_iy_{1i}(t) + c_{ij}(y_{1i}(t))f_j(y_{1j}(t)) + d_{ij}(y_{1i}(t))f_j(y_{1j}(t-\tau(t))) \\ \quad +I_i(t) + u_{2i}(t) \end{cases} \tag{6}$$

The synchronization errors as

$$e_{1i} = y_{1i} - x_{1i}e_{2i} = y_{2i} - x_{2i} \tag{7}$$

Then we have

$$\begin{cases} \dot{e}_{1i}(t) = e_{2i}(t) + u_{1i}(t) \\ \dot{e}_{2i}(t) = -a_ie_{2i}(t) - b_ie_{1i}(t) + F_i(t) + u_{2i}(t) \end{cases} \tag{8}$$

where,

$$\begin{array}{c} F_i(t) = c_{ij}(y_{1i}(t))f_j(y_{1j}(t)) - c_{ij}(x_{1i}(t))f_j(x_{1j}(t)) \\ +d_{ij}(y_{1i}(t))f_j(y_{1j}(t-\tau(t))) - d_{ij}(x_{1i}(t))f_j(x_{1j}(t-\tau(t))) \end{array} \tag{9}$$

To design the finite time and fixed-time synchronization theory, some lemmas are proposed based on a general nonlinear system

$$\dot{x} = f(x) \tag{10}$$

where x is error system state.

**Lemma 1.** *For* $x_i \in R\text{and}x_i \leq 0, i = 1, 2, \ldots, n, 0 < p < 1, q > 1,$ *then*

$$\left(\sum_{i=1}^{n} x_i\right)^p \leq \sum_{i=1}^{n} x_i{}^p \tag{11}$$

$$n^{1-q}\left(\sum_{i=1}^{n} x_i\right)^q \leq \sum_{i=1}^{n} x_i{}^q \tag{12}$$

**Lemma 2.** *Suppose the positive definite and continuous function* $V(t)$ *meets the following differential inequality* $f\dot{V}(t) \leq -\rho V^{\eta}(t), t \geq 0, V(0) \geq 0,$ *where* $0 < \eta < 1$ *and* $\rho > 0$ *are constants. Then,* $V(t)$ *meets the following inequality* $V^{1-\eta}(t) \leq V^{1-\eta}(0) - \rho(1-\eta)$, $0 \leq t \leq T$. *Then the origin of system (10) can achieve finite time stability, and* $T \leq \frac{V^{1-\eta}(0)}{\rho(1-\eta)}$

**Lemma 3.** *Suppose that* $V(\mathring{u}) : R^n \to R + \cup 0$ *is a continuous radically unbounded function and the following two conditions hold:*

*(1)*$V(x) = 0 \Leftrightarrow x = 0$

*(2)Any solution* $x(t)$ *of system equation reference goes here satisfies,*$V(x(t)) \leq -aV^p(x(t)) - bV^q(x(t))$, *for some* $a, b > 0, 0 \leq p < 1andq > 1$. *Then the origin of system (10) can achieve fixed-time stability, and* $T_{\max} = \frac{1}{a(1-p)} + \frac{1}{b(q-1)}$

## 3 Synchronization control

To derive the finite time synchronization criteria, the finite time synchronized feedback controller.

**Theorem 1.** *Choose the synchronization controller as following:*

$$\begin{cases} u_{1i}(t) = -e_{2i}(t) - k_{1i}e_{1i}^{\eta} \\ u_{2i}(t) = a_i e_{2i}(t) + b_i e_{1i}(t) - F_i(t) - k_{2i}e_{2i}^{\eta} \end{cases} \tag{13}$$

*where* $0 < \eta < 1$, *then, drive system (1) and response system (5) can achieve finite time synchronization, furthermore, finite time is*

$$T \leq \frac{V^{\frac{1-\eta}{2}}(0)}{2k(1-\eta)} \tag{14}$$

**Proof 1.** *Choose the Lyapunov candidate functional:*

$$V = \sum_{i=1}^{n} e_{1i}^2(t) + \sum_{i=1}^{n} e_{2i}^2(t) \tag{15}$$

Calculate the derivative of V along the trajectories of the error system (8) as

$$\dot{V} = 2\sum_{i=1}^{n} \dot{e}_{1i}(t)\, e_{1i}(t) + 2\sum_{i=1}^{n} \dot{e}_{2i}(t)\, e_{2i}(t) \tag{16}$$

Based on the controller (10), the error system (8) can be get as

$$\begin{cases} \dot{e}_{1i}(t) = -k_{1i}e_{1i}^{\eta} \\ \dot{e}_{2i}(t) = -k_{2i}e_{2i}^{\eta} \end{cases} \tag{17}$$

Take (13) into (12) as

$$\dot{V} = -\sum_{i=1}^{n} 2k_{1i}e_{1i}^{\eta+1}(t) - \sum_{i=1}^{n} 2k_{2i}e_{2i}^{\eta+1}(t) \leq -kV^{\frac{\eta+1}{2}} \tag{18}$$

where $k = \min(k_{1i}, k_2 i)$, based on Lemma 2, the error system is finite time asymptotic stable is $T \leq \frac{V^{\frac{1-\eta}{2}}(0)}{2k(1-\eta)}$, the proof is completed.

**Theorem 2.** *Choose the synchronization controller as following:*

$$\begin{cases} u_{1i}(t) = -e_{2i}(t) - k_{1i}e_{1i}^{p} - l_{1i}e_{1i}^{q} \\ u_{2i}(t) = a_i e_{2i}(t) + b_i e_{1i}(t) - F_i(t) - k_{2i}e_{2i}^{p} - l_{2i}e_{2i}^{q} \end{cases} \tag{19}$$

**Proof 2.** *Choose the Lyapunov candidate functional:*

$$V = \sum_{i=1}^{n} e_{1i}^2(t) + \sum_{i=1}^{n} e_{2i}^2(t) \tag{20}$$

Calculate the derivative of V along the trajectories of the error system (8) as

$$\dot{V} = 2\sum_{i=1}^{n} \dot{e}_{1i}(t)\, e_{1i}(t) + 2\sum_{i=1}^{n} \dot{e}_{2i}(t)\, e_{2i}(t) \tag{21}$$

Based on the controller (10), the error system (8) can be get as

$$\begin{cases} \dot{e}_{1i}(t) = -k_{1i}e_{1i}^{p} - l_{1i}e_{1i}^{q} \\ \dot{e}_{2i}(t) = -k_{2i}e_{2i}^{p} - l_{2i}e_{2i}^{q} \end{cases} \tag{22}$$

Take (13) into (12) as

$$\dot{V} = -\sum_{i=1}^{n} 2k_{1i}e_{1i}^{p+1}(t) - \sum_{i=1}^{n} 2k_{2i}e_{2i}^{p+1}(t) - \sum_{i=1}^{n} 2l_{1i}e_{1i}^{q+1}(t) - \sum_{i=1}^{n} 2l_{2i}e_{2i}^{q+1}(t) \tag{23}$$

Based on Lemma 1

$$\sum_{i=1}^{n} 2k_{1i}e_{1i}^{p+1} + \sum_{i=1}^{n} 2k_{2i}e_{2i}^{p+1} \geq a\left(\sum_{i=1}^{n}\left(e_{1i}^2\right)^{\frac{p+1}{2}} + \sum_{i=1}^{n}\left(e_{2i}^2\right)^{\frac{p+1}{2}}\right) \geq a\left(\sum_{i=1}^{n} e_{1i}^2 + \sum_{i=1}^{n} e_{2i}^2\right)^{\frac{p+1}{2}} \tag{24}$$

where $a = \min(k_{1i}, k_{2i})$.

$$\sum_{i=1}^{n} 2l_{1i}e_{1i}^{q+1}(t) + \sum_{i=1}^{n} 2l_{2i}e_{2i}^{q+1}(t) \geq b_1\left(\sum_{i=1}^{n}\left(e_{1i}^2\right)^{\frac{q+1}{2}} + \sum_{i=1}^{n}\left(e_{2i}^2\right)^{\frac{q+1}{2}}\right) \geq b\left(\sum_{i=1}^{n} e_{1i}^2 + \sum_{i=1}^{n} e_{2i}^2\right)^{\frac{q+1}{2}} \tag{25}$$

where , $b = (2n)^{\frac{1-q}{2}} b_1, b_1 = \min(2l_{1i}, 2l_{2i})$, therefore we have

$$\dot{V} \leq -aV^{\frac{p+1}{2}} - bV^{\frac{q+1}{2}} \tag{26}$$

Based on Lemma 3, the error system is fixed-time asymptotic stable is $T_{\max} = \frac{2}{a(1-p)} + \frac{2}{b(q-1)}$, the proof is completed.

# 4 Numerical simulations

In this section, we will use an example to illustrate how to apply the theory results proposed in this brief in applications. The chaotic neural network proposed is adopted as the drive system:

$$\dot{x}(t) = -d_i x_i(t) + \sum\nolimits_{j=1}^{3} a_{ij}(x_i(t))\, f_i(x_j(t)) + \sum\nolimits_{j=1}^{3} b_{ij}(x_i(t))\, \mathrm{g}_j(x_j(t-\tau_j(t))) \tag{27}$$

The corresponding response system as follows

$$\dot{y}_i(t) = -d_i y_i(\mathrm{t}) + \sum\nolimits_{j=1}^{n} a_{ij}(y_i(t))\, f_i(y_j(t)) + \sum\nolimits_{j=1}^{n} b_{ij}(y_i(t))\, \mathrm{g}_j(y_j(t-\tau_j(t))) + u_i(t) \tag{28}$$

where,

$$a_{11}(x_1)=\begin{cases}1.2, |x_1|\le 1\\ 1.8, |x_1|>1\end{cases}, a_{12}(x_1)=\begin{cases}-2.1, |x_1|\le 1\\ -1.6, |x_1|>1\end{cases}, a_{13}(x_1)=\begin{cases}2.1, |x_1|\le 1\\ 1.6, |x_1|>1\end{cases}$$
$$a_{21}(x_2)=\begin{cases}-3.6, |x_2|\le 1\\ -2.3, |x_2|>1\end{cases}, a_{22}(x_2)=\begin{cases}1.4, |x_2|\le 1\\ 2.3, |x_2|>1\end{cases}, a_{23}(x_2)=\begin{cases}-1.4, |x_2|\le 1\\ -2.2, |x_2|>1\end{cases}$$
$$a_{31}(x_3)=\begin{cases}1.6, |x_3|\le 1\\ 1.3, |x_3|>1\end{cases}, a_{32}(x_3)=\begin{cases}1.4, |x_3|\le 1\\ 2.1, |x_3|>1\end{cases}, a_{33}(x_3)=\begin{cases}1.5, |x_3|\le 1\\ 2.2, |x_3|>1\end{cases}$$
$$b_{11}(x_1)=\begin{cases}1.1, |x_1|\le 1\\ 1.7, |x_1|>1\end{cases}, b_{12}(x_1)=\begin{cases}1.5, |x_1|\le 1\\ 1.2, |x_1|>1\end{cases}, b_{13}(x_1)=\begin{cases}1.5, |x_1|\le 1\\ 1.2, |x_1|>1\end{cases}$$
$$b_{21}(x_2)=\begin{cases}1.3, |x_2|\le 1\\ 1.1, |x_2|>1\end{cases}, b_{22}(x_2)=\begin{cases}-1.2, |x_2|\le 1\\ -2.2, |x_2|>1\end{cases}, b_{23}(x_2)=\begin{cases}-1.1, |x_2|\le 1\\ -2.3, |x_2|>1\end{cases}$$
$$b_{31}(x_3)=\begin{cases}2.6, |x_3|\le 1\\ 2.3, |x_3|>1\end{cases}, b_{32}(x_3)=\begin{cases}2.4, |x_3|\le 1\\ 2.1, |x_3|>1\end{cases}, b_{33}(x_3)=\begin{cases}3.5, |x_3|\le 1\\ 3.2, |x_3|>1\end{cases}$$

The activation functions and time-varying delays are taken as $f(x) = g(x) = \tanh(x)$.

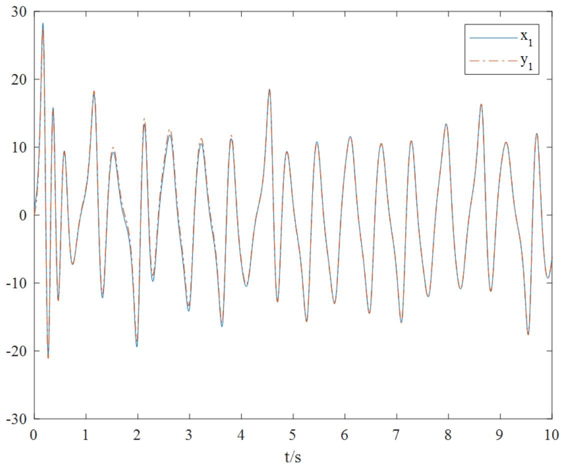


Figure 1: Time evolution of variable of coupled neural networks $x_1, y_1$

The time delay $\tau = 1$, the initial condition choose as $x_1(0) = 3, x_2(0) = 5, y_1(0) = 4, y_2(0) = 7$. Based on Theorem 1, choose the control gain as $\eta = 1/3, k = 0.3$, then the error system is finite time stable. The simulated results are shown in Figure 1 and Figure 2, indicate the response system synchronizes the driver system in finite time.

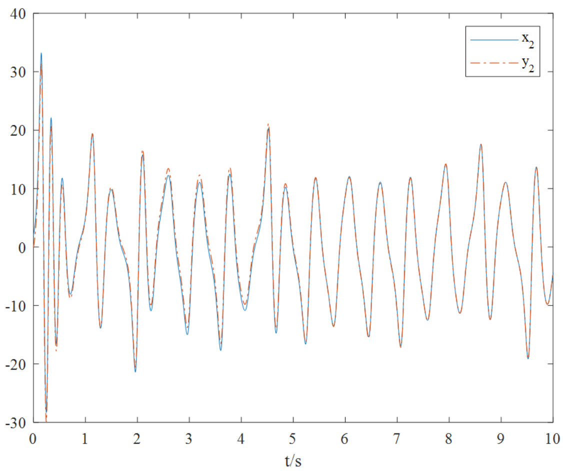


Figure 2: Time evolution of variable of coupled neural networks $x_2, y_2$

The time delay $\tau = 1$, the initial condition choose as $x_1(0) = 3, x_2(0) = 5, y_1(0) = 4, y_2(0) = 7$. Based on Theorem 2, choose the control gain as $p = 1/3, q = 5/3, k = 1$, then the error system is fixed-time stable. The simulated results are shown in Figure 3 and Figure 4, indicate the response system synchronizes the driver system in fixed time. Simulation result indicated effectiveness and feasibility of the proposed control method.

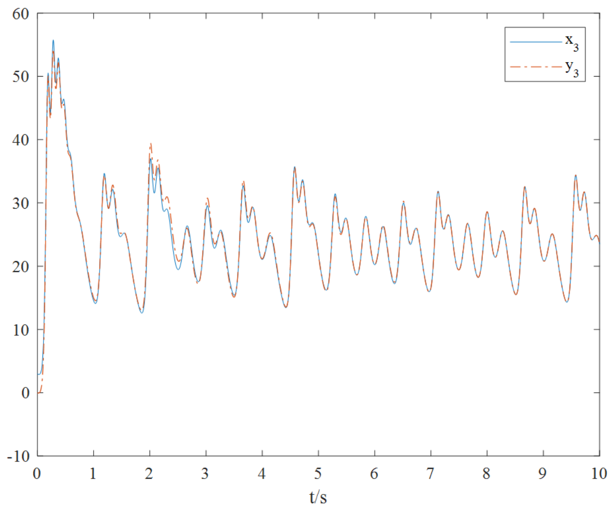


Figure 3: Time evolution of variable of coupled neural networks $x_3, y_3$

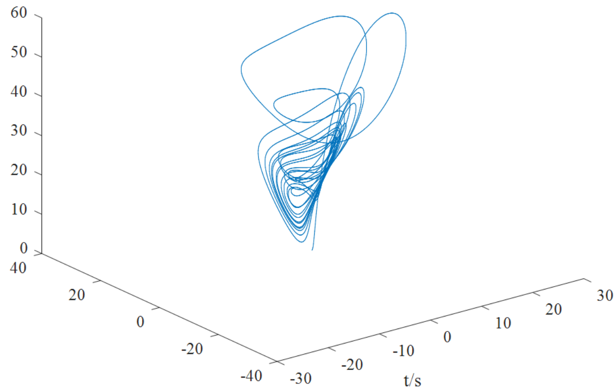


Figure 4: Chaotic attractor of neural networks

## 5 Conclusion

In this paper, the problem of finite time and fixed time synchronization of a class of chaotic neural networks has been considered. The method introduced for linear feedback finite time and fixed time control is very effective, and it is simple to implement in practice. Based on Lyapunov stability theory, finite time and fixed time stability is proved. To the end, numerical simulation is given to show the effectiveness and feasibility of the developed method.

## References

[1] Cao, J.; Wang, J. (2003). Global asymptotic stability of a general class of recurrent neural networks with time-varying delays, *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, 50(1), 34-44, 2003.

[2] Chu, X.; Xu, L.; Hu, H. (2020). Exponential quasi-synchronization of conformable fractional-order complex dynamical networks, *Chaos, Solitons & Fractals*, 140, 110268, 2020.

[3] Cui, W.; Wang, Z.; Jin, W. (2020). Fixed-time synchronization of Markovian jump fuzzy cellular neural networks with stochastic disturbance and time-varying delays, *Fuzzy Sets and Systems, in press*, 2020.

[4] Fadel, M.Z.; Rabie, M.G.; Youssef, A.M. (2019). Modeling, simulation and control of a fly-by-wire flight control system using classical PID and modified PI-D controllers, *Journal Européen des Systèmes Automatisés*, 52(3), 267-276, 2019.

[5] Gan, Y.; Liu, C.; Peng, H.; Liu, F.; Rao, H. (2020). Anti-synchronization for periodic bam neural networks with Markov scheduling protocol, *Neurocomputing*, 417, 585-592, 2020.

[6] Ke, L. (2020). Synchronization control of high-order inertial Hopfield neural network with time delay, *Revue d'Intelligence Artificielle*, 34(5), 595-600, 2020.

[7] Lee, T.H.; Lim, C.P.; Nahavandi, S.; Park, J.H. (2018). Network-based synchronization of T–S fuzzy chaotic systems with asynchronous samplings, *Journal of the Franklin Institute*, 355(13), 5736-5758, 2018.

[8] Li, J.Y.; Zhang, B.; Lu, R.; Xu, Y.; Rao, H.X. (2020). Synchronization for markovian coupled neural networks with partial mode observation: The finite-time case, *Journal of the Franklin Institute*, 357(17), 12767-12786, 2020.

[9] Lü, L.; Wei, Q.; Jia, H.; Tian, S.; Xu, Z.; Zhao, L.; Xu, Z.; Xu, X. (2019). Parameter identification and synchronization between uncertain delay networks based on the coupling technology, *Physica A: Statistical Mechanics and its Applications*, 534, 120713, 2019.

[10] Lu, X.; Wu, Q.; Zhou, Y.; Ma, Y.; Song, C.; Ma, C. (2019). A dynamic swarm firefly algorithm based on chaos theory and Max-Min distance algorithm, *Traitement du Signal*, 36(3), 227-231, 2019.

[11] Pan, C.; Bao, H. (2020). Exponential synchronization of complex-valued memristor-based delayed neural networks via quantized intermittent control, *Neurocomputing*, 404, 317-328, 2020.

[12] Pecora, L.M.; Carroll, T.L. (1990). Synchronization in Chaotic Systems, *Physical Review Letters*, 64(8), 821, 1990.

[13] Pi, J.; Zhang, W.; Zhang, S.; Pi, C.; Xie, C. (2019). A separated adaptive control strategy for different conditions based on flexible dynamics equation of robot manipulator, *Journal Européen des Systèmes Automatisés*, 52(6), 575-585, 2019.

[14] Rafikov, M.; Balthazar, J.M. (2008). On control and synchronization in chaotic and hyperchaotic systems via linear feedback control, *Communications in Nonlinear Science and Numerical Simulation*, 13(7), 1246-1255, 2008.

[15] Schijven, D.; Stevelink, R.; McCormack, M.; van Rheenen, W.; Luykx, J.J.; Koeleman, B.P.; Veldink, J.H.; Project MinE ALS Project MinE ALS GWAS Consortium. (2020). Analysis of shared common genetic risk between amyotrophic lateral sclerosis and epilepsy, *Neurobiology of Aging*, 92, 153-e1, 2020.

[16] Song, X.; Man, J.; Song, S.; Zhang, Y.; Ning, Z. (2020). Finite/fixed-time synchronization for Markovian complex-valued Memristive neural networks with reaction–diffusion terms and its application, *Neurocomputing*, 414, 131-142, 2020.

[17] Sun, B.; Cao, Y.; Guo, Z.; Yan, Z.; Wen, S. (2020). Synchronization of discrete-time recurrent neural networks with time-varying delays via quantized sliding mode control, *Applied Mathematics and Computation*, 375, 125093, 2020.

[18] Wang, H.D. (2010). A synchronous transmission method for array signals of sensor network under resonance technology, *Traitement du Signal*, 37(4), 579-584, 2020.

[19] Wang, W.; Fan, Y. (2015). Synchronization of Arneodo chaotic system via backstepping fuzzy adaptive control, *Optik*, 126(20), 2679-2683, 2015.

[20] Wang, W.; Tian, K.; Zhang, J. (2020). Dynamic modelling and adaptive control of automobile active suspension system, *Journal Européen des Systèmes Automatisés*, 53(2), 297-303, 2020.

[21] Yang, L.; Huang, T.; Deng, L.; Zeng, Y.; Huang, S. (2019). Analysis on chaotic mechanism of direct-drive permanent magnet synchronous generators based on Lyapunov stability theory, *European Journal of Electrical Engineering*, 21(6), 531-537, 2019.

[22] Zhang, Y.; Han, Q.L. (2012). Network-based synchronization of delayed neural networks, *IEEE Transactions on Circuits and Systems I: Regular Papers*, 60(3), 676-689, 2013.

[23] Zheng, B.; Hu, C.; Yu, J.; Jiang, H. (2020). Finite-time synchronization of fully complex-valued neural networks with fractional-order, *Neurocomputing*, 373, 70-80, 2020.

Copyright ©2020 by the authors. Licensee Agora University, Oradea, Romania.
This is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International License.
Journal's webpage: http://univagora.ro/jour/index.php/ijccc/

C O P E
Member since 2012
JM08090

This journal is a member of, and subscribes to the principles of,
the Committee on Publication Ethics (COPE).
https://publicationethics.org/members/international-journal-computers-communications-and-control

*Cite this paper as:*

Pang, Y.J.; Dong, S.M. (2021). Finite time Synchronization of Inertial Memristive Neural Networks with Time Varying Dela, *International Journal of Computers Communications & Control*, 16(4), 4215, 2021.

https://doi.org/10.15837/ijccc.2021.4.4215