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A novel memristive neural network with hidden attractors and its circuitry implementation

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Neural networks have been applied in various fields from signal processing, pattern recognition, associative memory to artificial intelligence. Recently, nanoscale memristor has renewed interest in experimental realization of neural network. A neural network with a memristive synaptic weight is studied in this work. Dynamical properties of the proposed neural network are investigated through phase portraits, Poincaré map, and Lyapunov exponents. Interestingly, the memristive neural network can generate hyperchaotic attractors without the presence of equilibrium points. Moreover, circuital implementation of such memristive neural network is presented to show its feasibility.

neural network, memristor, hyperchaos, hidden attractor, equilibrium

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1 Introduction

Neural network and neurodynamics have been studied and had a variety of applications in science and engineering, i.e. character recognition, image compression, stock market prediction, system control, electronic nose, etc. [1–16]. Especially, Hopfield type neural network received significant attention in neurocomputing because it can describe brain dynamics and provide a model for understanding human memory [17–22].

Recently, various researches focus on the realization of synaptic weights in neural network by using the memristor, the fourth circuit element besides resistor, capacitor and inductor [23–28]. Memristor is considered as a potential candidate to replicate the behavior of neuron's synapse because of its nanoscale size and its nonlinear characteristics [29–31]. Moreover, the peculiar features of the memristor can generate complex dynamics in neural networks, like chaos. Buscarino et al. introduced memristive chaotic circuits based on cellular nonlinear networks [32]. Hyperchaos was studied on a small memristive neural network [33], which has an unlimited number of equilibrium points. In addition, this small memristive network belongs to a new class of systems with hidden attractor [34–36]. Investigation of hidden attractors in dynamical systems is important in academic community and practical problems [37–46].

Motivated by special features of memristor, the simplicity of Hopfield type neural network and rare presence of

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hidden attractors, a novel memristive network with hidden attractor is studied in this paper.

This paper is organized as follows: Section 2 proposes the model of the novel memristive neural network. Its fundamental dynamics are presented in Section 3, while its circuital implementation is discovered in Section 4. Finally, conclusions are drawn in the last Section.

2 Model of the new memristive neural network

It has been known that a Hopfield neural network can be described by circuital equations of each neuron [17,33]. Therefore, a Hopfield neural network including n neurons is given by

$$C_i\dot{x}_i = -\frac{x_i}{R_i} + \sum_{j=1}^{n} w_{ij}v_j + I_i, \tag{1}$$

where the state x_i of the i-th neuron represents the voltage on the capacitor C_i. Here, R_i is the membrane resistance between the inside and outside of the neuron and the input bias current is denoted as I_i. The matrix $\boldsymbol{W}=(w_{ij})$ is defined as synaptic weight matrix which presents the strength of connection between neurons. The voltage input from the j-th neuron v_j [17,33] is given by

$$v_j = \tanh\left(x_j\right). \tag{2}$$

In this work, we consider a Hopfield type neural network including three neurons as shown in Figure 1. It is noting that there is a flux-controlled memristor [23,24,27] which plays the role of a synaptic weight. The dynamical equations of the flux controlled memristor have the following form:

$$\begin{cases} i_M = W(\varphi)v_M, \\ \dot{\varphi} = v_M, \end{cases} \tag{3}$$

where v_M and i_M are the voltage across the memristor and the current through the memristor, respectively. The memductance $W(\varphi)$ is defined as

$$W(\varphi) = \frac{\mathrm{d}q(\varphi)}{\mathrm{d}\varphi} = a\varphi + b\varphi^2, \tag{4}$$

where q and φ are the charge and magnetic flux, while a, b are parameters.

From eqs. (1) and (2), let $C_i = 1$, $R_i = 1$, dynamical equations of the new memristive neural networks are derived as

$$\begin{cases} \dot{x}_i = -x_i + \sum_{j=1}^{3} w_{ij}v_j + I_i, \\ \dot{\varphi} = \tanh\left(x_1\right), \end{cases} \tag{5}$$

where $i = 1, 2, 3$ while the synaptic weight matrix is

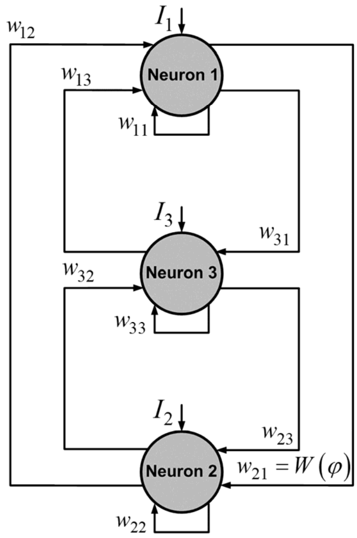

Figure 1 Neural network including a memristive synaptic weight.

$$\boldsymbol{W} = \left(w_{ij}\right) = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} = \begin{bmatrix} 1.6 & 2 & 1 \\ a\varphi + b\varphi^2 & 1.5 & 0 \\ 3 & -2 & 1 \end{bmatrix}. \tag{6}$$

In addition, the input bias current term is selected as

$$\boldsymbol{I} = \left[I_1, I_2, I_3\right]^{\mathrm{T}} = \left[0, 0, c\right]^{\mathrm{T}}, \tag{7}$$

where c is the parameter which indicates the input current at the third neuron.

3 Dynamics of the memristive neural network

When $c = 0$, the memristive neural network (5) has the line equilibrium $E(0, 0, 0, \varphi)$. In addition, neural network (5) can generate hyperchaos for different values of a and b. For example, hyperchaos is observed when selecting $a = -0.001$, $b = -0.05$, and the initial conditions condition $(x_1(0), x_2(0), x_3(0), \varphi(0)) = (0, 0.01, 0.01, 0)$. In this case, the calculated Lyapunov exponents are $\lambda_1 = 0.0309$, $\lambda_2 = 0.0106$, $\lambda_3 = 0$, and $\lambda_4 = -0.1178$.

When $c \neq 0$, it is easy to see that neural network (5) has no equilibrium points. It is interesting that the novel neural network (5) can still exhibit hyperchaos when choosing the parameters $a = -0.001$, $b = -0.05$, $c = -0.001$, and the initial conditions condition $(x_1(0), x_2(0), x_3(0), \varphi(0)) = (0, 0.01, 0.01, 0)$. Hyperchaotic attractors are presented in Figure 2.

In this case, the calculated Lyapunov exponents are $\lambda_1 = 0.0291$, $\lambda_2 = 0.0095$, $\lambda_3 = 0$, and $\lambda_4 = -0.1140$. Therefore, memristive neural network (5) is a hyperchaotic system with hidden attractor [34–36]. This special case will be discussed in next sections.

The Kaplan-Yorke fractional dimension [47], presenting the complexity of attractor, is given by

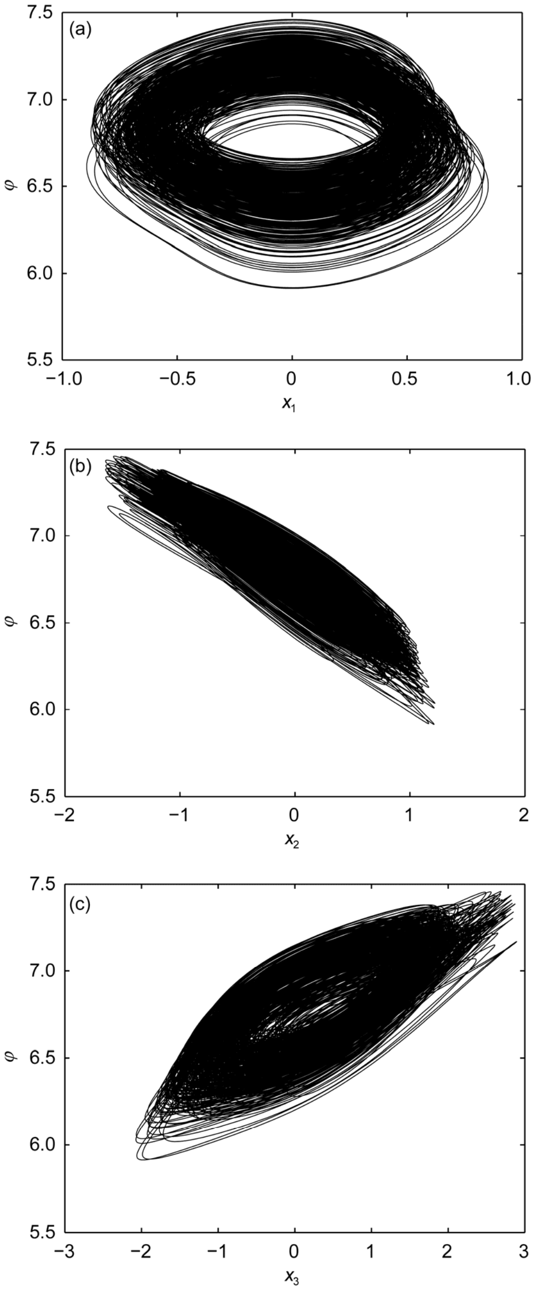

Figure 2 The projection of the hyperchaotic attractor in the memristive neural network (5) for a=–0.001, b=–0.05, and c=–0.001. (a) in the x_1–φ phase plane, (b) in the x_2–φ phase plane, and (c) in the x_3–φ phase plane.

$$D_{KY} = j + \frac{1}{|\lambda_{j+1}|}\sum_{i=1}^{j}\lambda_i,$$

where j is the largest integer satisfying $\sum_{i=1}^{j}\lambda_i \geqslant 0$ and $\sum_{i=1}^{j+1}\lambda_i < 0$. The calculated fractional dimension of neural network (5) when a = –0.001, b = –0.05, and c = –0.001 is D_{KY} = 3.3386. This fractional dimension indicates a strange attractor. The Poincaré map in Figure 3 also shows the rich dynamical behavior of the proposed memristive neural network (5).

In order to get better insight into dynamics of the new neural network, its Lyapunov exponents have been calculated by using the well-known Wolf's algorithm [48–50]. Three largest Lyapunov exponents of memristive neural network (5) are shown in Figure 4 when varying the value of the parameter c. Although the positive Lyapunov exponent does not mean chaos every time [51,52], there is no ambiguity on the indication of chaos in our regular work.

It is interesting to consider a new simple system by changing the tangent hyperbolic function in system (5) to a similar function like the signum function. Although the obtained system is still a no-equilibrium one, it cannot exhibit chaos.

4 Circuit realization

Implementing chaotic/hyperchaotic systems by using elec-

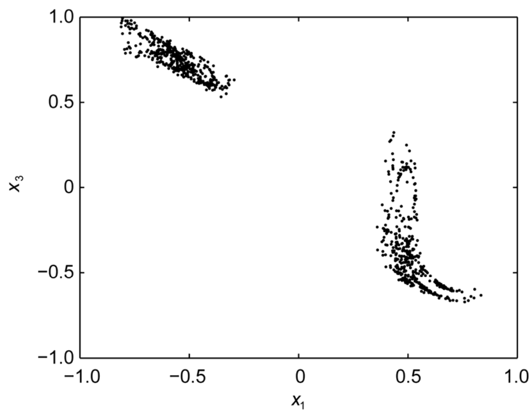

Figure 3 Poincaré map in the plane x_1–x_3 when x_2=0 for a=–0.001, b=–0.05, and c=–0.001.

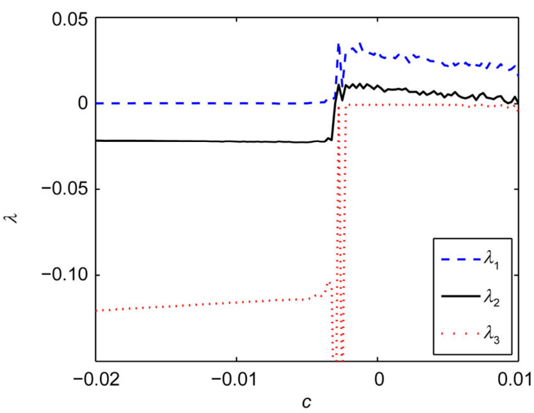

Figure 4 (Color online) Three largest Lyapunov exponents λ_1 (dash line), λ_2 (solid line), λ_3 (red dot line) of neural network (5) when changing the parameter c for a = –0.001, and b = –0.05.

tronic circuits is an effective approach for discovering dynamics of such systems [53,54]. Moreover, realization of circuits based on theoretical chaotic models has practical applications such as in cryptography, image encryption, random bit generator, or path planning for mobile robot [55–58]. Especially, circuital implementation is one of vital existing technologies to produce specialized analog neural networks or neuron models [59–65].

In this section, an electronic circuit is proposed to implement the memristive neural network (5). Using an approach based on operational amplifiers [54,66–69], the circuit is designed as shown in Figure 5. The variables x_1, x_2, x_3, φ of neural network (5) correspond to the voltages across the capacitor C_1, C_2, C_3, and C_4. As can be seen in Figure 5, there are three blocks, denoted as –TANH(), which implement the inverting tangent hyperbolic functions. The detail of each block is presented in Figure 6. It is easy to see that the inverting tangent hyperbolic function can be achieved by a dual-transistor pair [70,71].

By applying Kirchhoff's circuit laws to the electronic circuit in Figure 5, its circuital equations can be derived as follows

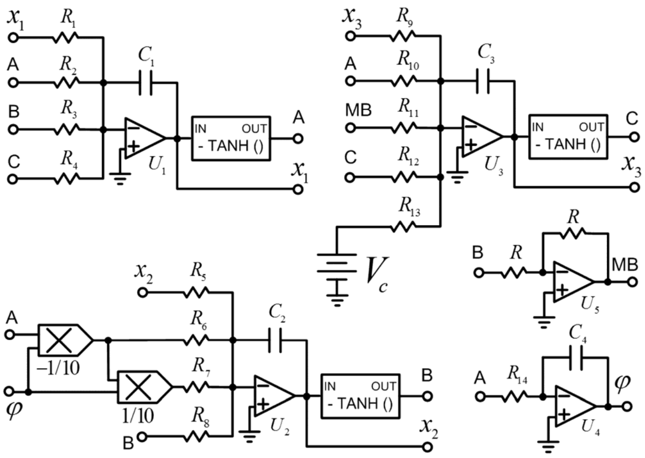

Figure 5 Designed circuit of the memristive neural network with hidden attractor (5).

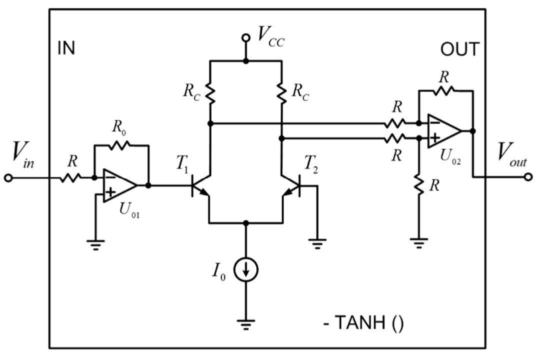

Figure 6 Schematic of the circuit which generates the inverting tangent hyperbolic function. Here the value of the constant current source I_0 is 1.1 mA.

$$\begin{cases} \dot{x}_1 = -\dfrac{1}{R_1C_1}x_1 + \dfrac{1}{R_2C_1}\tanh(x_1) + \dfrac{1}{R_3C_1}\tanh(x_2) \\ \quad + \dfrac{1}{R_4C_1}\tanh(x_3), \\ \dot{x}_2 = -\dfrac{1}{R_5C_2}x_2 - \dfrac{1}{10C_2}\left(\dfrac{1}{R_6}\varphi + \dfrac{1}{10R_7}\varphi^2\right)\tanh(x_1) \\ \quad + \dfrac{1}{R_8C_2}\tanh(x_2), \\ \dot{x}_3 = -\dfrac{1}{R_9C_3}x_3 + \dfrac{1}{R_{10}C_3}\tanh(x_1) - \dfrac{1}{R_{11}C_3}\tanh(x_2) \\ \quad + \dfrac{1}{R_{12}C_3}\tanh(x_3) - \dfrac{1}{R_{13}C_3}V_C, \\ \dot{\varphi} = \dfrac{1}{R_{14}C_4}\tanh(x_1). \end{cases} \tag{8}$$

The operational amplifiers in this work are TL084 type ones, which are connected to power supplies ±15 Volts. The values of components are selected to match the values of parameters in neural network (5) and listed in Table 1.

The designed circuit is run in the electronic simulation package OrCAD. The transfer characteristic of the inverting tangent hyperbolic function is indicated in Figure 7. This

Table 1 The values of electronics components

Component name	Value	Unit
R_0	0.52	kΩ
R, R_1, R_4, R_5, R_9, R_{12}, R_{14}	10	kΩ
R_2	6.25	kΩ
R_3, R_{11}	5	kΩ
R_6, R_{13}	1	MΩ
R_7	2	kΩ
R_8	6.667	kΩ
R_{10}	3.333	kΩ
R_C	1	kΩ
C_1, C_2, C_3, C_4	10	nF
V_C	0.1	V_{DC}
V_{CC}	15	V_{DC}

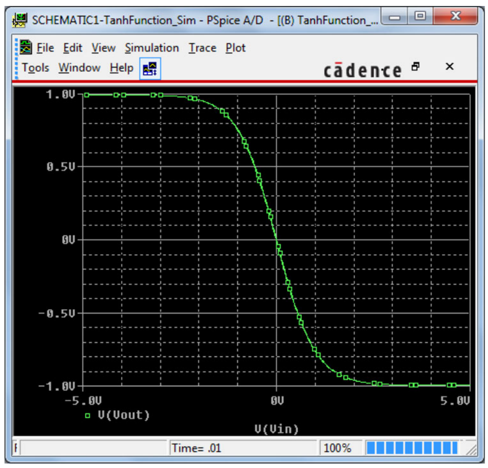

Figure 7 (Color online) Transfer characteristic of a –TANH() block obtained in PSpice.

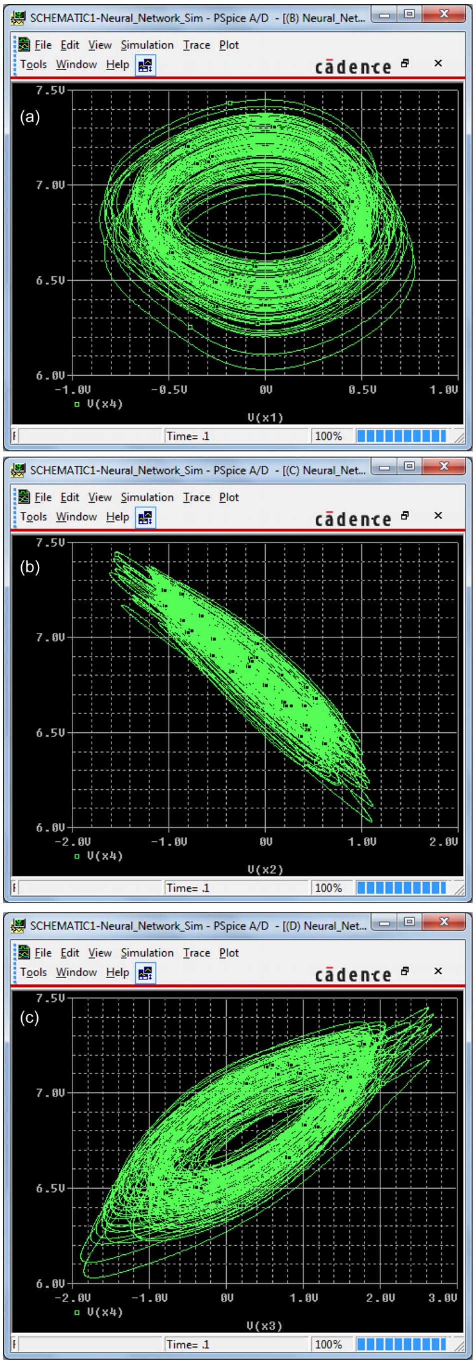

Figure 8 (Color online) Attractor obtained from the designed circuit by using OrCAD PSpice (a) in $v_{C1} - v_{C4}$ phase plane, (b) in $v_{C2} - v_{C4}$ phase plane, and (c) in $v_{C3} - v_{C4}$ phase plane.

transfer characteristic in PSpice agrees with the theoretical one. Also, the results in Figure 8 verify that the designed circuit in PSpice can generate hyperchaotic attractors similar to the numerical results in Figure 2.

5 Conclusion

This paper presents a memristive neural network. The presence of a memristive synaptic weight creates special features, i.e. having no equilibrium points, exhibiting hyperchaotic behavior, or being classified as a system with hidden attractor. In addition, the designed circuit shows the feasibility of the proposed memristive neural network. Moreover, hyperchaos of this neural network can be applied into practical chaos-based systems such as cryptosystems and secure communications in future works.

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1 Haykin S. Neural Network: A Comprehensive Foundation. New Jersey: Prentice Hall, 1998
2 Bishop C M. Neural Network for Pattern Recognition. Oxford: Clarendon Press, 1995
3 Yu W. Nonlinear system identification using discrete-time recurrent neural network with stable learning algorithms. Inf Sci, 2004, 158: 131–147
4 Rubio J, Yu W. Nonlinear system identification with recurrent neural networks and dead-zone Kalman filter algorithm. Neurocomputing, 2007, 70: 2460–2466
5 Wang Q, Zheng Y, Ma J. Cooperative dynamics in neuronal networks. Chaos Solitons Fractals, 2013, 56: 19–27
6 Qin H X, Ma J, Jin W Y, et al. Dynamics of electric activities in neuron and neurons of network induced by autapses. Sci China Tech Sci, 2014, 57: 936–946
7 Gu H G, Chen S G. Potassium-induced bifurcations and chaos of firing patterns observed from biological experiment on a neural pacemaker. Sci China Tech Sci, 2014, 57: 864–871
8 Qin H, Ma J, Wang C, et al. Autapse-induced target wave, spiral wave in regular network of neurons. Sci China-Phys Mech Astrom, 2014, 57: 1918–1926
9 Wang H X, Wang Q Y, Zheng Y H. Bifurcation analysis for Hindmarsh-Rose neuronal model with time-delayed feedback control and application to chaos control. Sci China Tech Sci, 2014, 57: 872–878
10 Song Z G, Xu J. Stability switches and Bogdanov-Takens bifurcation in an inertial two-neuron coupling system with multiple delays. Sci China Tech Sci, 2014, 57: 893–904
11 Wu A L, Zeng Z G. Anti-synchronization control of a class of memristive recurrent neural networks. Commun Nonlinear Sci Numer Simul, 2013, 18: 373–385
12 Itoh M, Chua L O. Autoassociative memory cellular neural networks. Int J Bifurcat Chaos, 2010, 20: 3225–3266
13 Sun X J, Shi X. Effects of channel blocks on the spiking regularity in clustered neuronal networks. Sci China Tech Sci, 2014, 57: 879–884
14 Zhou L, Wu X J, Liu Z R. Distributed coordinated adaptive tracking in networked redundant robotic systems with a dynamic leader. Sci China Tech Sci, 2014, 57: 905–913
15 Xie Y, Kang Y M, Liu Y, et al. Firing properties and synchronization rate in fractional-order Hindmarsh-Rose model neurons. Sci China Tech Sci, 2014, 57: 914–922
16 Ye W J, Liu S Q, Liu X L. Synchronization of two electrically coupled inspiratory pacemaker neurons. Sci China Tech Sci, 2014, 57: 929–935
17 Hopfield J J. Neurons with graded response have collective computational properties like those of 2-state neurons. P Natl Acad Sci USA, 1984, 81: 3088–3092
18 Yang X S, Huang Y. Complex dynamics in simple Hopfield neural networks. Chaos, 2006, 16: 033114

19 Li Q D, Yang X S, Yang F Y. Hyperchaos in Hopfield-type neural networks. Neurocomputing, 2005, 67: 275–280
20 Storkey A J, Valabregue R. The basins of attractor of a new Hopfield learning rule. Neural Netw, 1999, 12: 869–876
21 Zheng P, Tang W, Zhang J. Dynamic analysis of unstable Hopfield networks. Nonlinear Dyn, 2010, 61: 399–406
22 Bersini H, Sener P. The connections between the frustrated chaos and the intermittency chaos in small Hopfield networks. Neural Netw, 2002, 15: 1197–1204
23 Chua L O. Memristor–missing circuit element. IEEE T Circuit Theory, 1971, 18: 507–519
24 Chua L O, Kang S M. Memristive devices and systems. Proc IEEE 1976, 64: 209–223
25 Adhikari S P, Yang C, Kim H, et al. Memristor bridge synapse-based neural network and its learning. IEEE T Neural Netw Learning Syst, 2012, 23: 1426–1435
26 Kim H, Sah M P, Yang C, et al. Neural synaptic weighting with a pulse-based memristor circuit. IEEE T Circuits-I, 2012, 59: 148–158
27 Tetzlaff R. Memristors and Memristive Systems. New York: Springer, 2014
28 Wu A L, Zhang J, Zeng Z G. Dynamic behaviors of a class of memristor-based Hopfield networks. Phys Lett A, 2011, 375: 1661–1665
29 Strukov D B, Snider G S, Stewart D R, et al. The missing memristor found. Nature, 2008 453: 80–83
30 Shin S, Kim K, Kang S M. Memristor applications for programmable analog ICs. IEEE T Nanotechnology, 2011, 10: 266–274
31 Pershin Y V, Di Ventra M. Experimental demonstration of associative memory with memristive neural networks. Neural Netw, 2010, 23: 881–886
32 Buscarino A, Fortuna L, Frasca M, et al. Memristive chaotic circuits based on cellular nonlinear networks. Int J Bifurcat Chaos, 2012, 22: 1250070
33 Li Q, S. Tang, Zeng H, et al. On hyperchaos in a small memristive neural network. Nonlinear Dyn, 2014, 78: 1087–1099
34 Leonov G A, Kuznetsov N V, Vagaitsev V I. Localization of hidden Chua's attractors. Phys Lett A, 2011, 375: 2230–2233
35 Leonov G A, Kuznetsov N V, Vagaitsev V I. Hidden attractor in smooth Chua system. Physica D, 2012, 241: 1482–1486
36 Leonov G A, Kuznetsov N V. Hidden attractors in dynamical systems: From hidden oscillation in Hilbert Kolmogorov, Aizerman and Kalman problems to hidden chaotic attractor in Chua circuits. Int J Bifurcat Chaos, 2013, 23: 1330002
37 Leonov G A, Kuznetsov N V, Kiseleva M A, et al. Hidden oscillations in mathematical model of drilling system actuated by induction motor with a wound rotor. Nonlinear Dyn, 2014, 77: 277–288
38 Molaie M, Jafari S, Sprott J C, et al. Simple chaotic ows with one stable equilibrium. Int J Bifurcat Chaos, 2013, 23: 1350188
39 Kingni S T, Jafari S, Simo H, et al. Three dimensional chaotic autonomous system with only one stable equilibrium: Analysis, circuit design, parameter estimation, control, synchronization and its fractional- order form. Eur Phys J Plus, 2014, 129: 76
40 Jafari S, Sprott J C. Simple chaotic ows with a line equilibrium. Chaos Solitons Fractals, 2013, 57: 79–84
41 Jafari S, Sprott J C, Golpayegani S M R H. Elementary quadratic chaotic ows with no equilibria. Phys Lett A, 2013, 377: 699–702
42 Pham V T, Jafari S, Volos C, et al. Is that really hidden? The presence of complex fixed-points in chaotic flows with no equilibria. Int J Bifurcat Chaos, 2014, 24: 14500146
43 Pham V T, Volos C, Jafari S, et al. Constructing a novel no-equilibrium chaotic system. Int J Bifurcat Chaos, 2014, 24: 1450073
44 Wang X, Chen G. A chaotic system with only one stable equilibrium. Commun Nonlinear Sci Numer Simul, 2012, 17: 1264–1272
45 Wang X, Chen G. Constructing a chaotic system with any number of equilibria. Nonlinear Dyn, 2013, 71: 429–436
46 Wei Z. Dynamical behaviors of a chaotic system with no equilibria. Phys Lett A, 2011, 376: 102–108
47 Frederickson P, Kaplan J L, Yorke H L, et al. The Lyapunov dimension of strange attractor. J Differential Equ, 1983, 49: 185–207
48 Wolf A, Swift J B, Swinney H L, et al. Determining Lyapunov exponents from a time series. Physica D, 1985, 16: 285–317
49 Kuznetsov N V, Alexeeva T A, Leonov G A. Invariance of Lyapunov characteristic exponents, Lyapunov exponents, and Lyapunov dimension for regular and non-regular linearization. ArXiv: 1401.2016v2, 2014
50 Leonov G A, Kuznetsov N V, Mokaev T N. Homoclinic orbits, and self-excited and hidden attractors in a Lorenz-like system describing convective fluid motion. Eur Phys J Special Topic, 2015, 224: 1421–1458
51 Leonov G A, Kuznetsov N V. Time-varying linearization and the Perron effects. Int J Bifurcat Chaos, 2007, 17: 1079–1107
52 Kuznetsov N V, Leonov G A. On stability by the first approximation for discrete systems. In: Proceedings of International Conference on Physics and Control, Saint Petersburg, the RUSSIA, 2005. 596–599
53 Ma J, Wu X, Chu R, et al. Selection of multi-scroll attractors in Jerk circuits and their verification using Pspice. Nonlinear Dyn, 2014, 76: 1951–1962
54 Buscarino A, Fortuna L, Frasca M. Experimental robust synchronization of hyperchaotic circuits. Physica D, 2009, 238: 1917-1922
55 Banerjee. Chaos Synchronization and Cryptography for Secure communications. USA: IGI Global, 2010
56 Volos C K, Kyprianidis I M, Stouboulus I N. A chaotic path planning generator for autonomous mobile robots. Robot Auton Syst, 2012, 60: 651–656
57 Volos C K, Kyprianidis I M, Stouboulus I N. Image encryption process based on chaotic synchronization phenomena. Signal Process, 2013, 93: 1328–1340
58 Volos C K, Kyprianidis I M, Stouboulus I N. Experimental investigation on coverage performance of a chaotic autonomous mobile robot. Robot Auton Syst, 2013, 61: 1314–1322
59 Li F, Liu Q, Guo H, et al. Simulating the electric activity of FitzHugh-Nagumo neuron by using Josephson junction model. Nonlinear Dyn, 2012, 69: 2169–2179
60 Wu X, Ma J, Yuan Li, et al. Simulating electric activities of neurons by using PSPICE. Nonlinear Dyn, 2014, 75: 113–126
61 Rabinovich M, Huerta R, Bazhenov M, et al. Computer simulations of stimulus dependent state switching in basic circuits of bursting neurons. Phys Rev E, 1998, 58: 6418
62 Sabir J, Stephane B, Jean-Marie B, et al. Synaptic coupling between two electronic neurons. Nonlinear Dyn, 2006, 44: 29–36
63 Abarbanel D I, Talathi S S. Neural circuitry for recognizing interspike interval sequences. Phys Rev Lett, 2006, 96: 148104
64 Sitt J D, Aliaga J. Versatile biologically inspired electronic. Phys Rev E, 2007, 76: 051919
65 Kwon O, Kim K, Park S, et al. Effects of periodic stimulation on an overly activated neuronal circuit. Phys Rev E, 2011, 84: 021911
66 Fortuna L, Frasca M, Xibilia M G. Chua’s Circuit Implementations: Yesterday, Today and Tomorrow. Singapore: World Scientific, 2009.
67 Vaidyanathan S, Pham V T, Volos C K. A 5-D hyperchaotic Rikitake dynamo system with hidden attractors. Eur Phys J Special Topic, 2015, 224: 1575–1592
68 Tahir F R, Sajad J, Pham V T, et al. A novel no-equilibrium chaotic system with multiwing butterfly attractors. Int J Bifurcat Chaos, 2015, 25: 1550056
69 Shahzad M, Pham V T, Ahmad M A, et al. Synchronization and circuit design of a chaotic system with coexisting hidden attractors. Eur Phys J Special Topic, 2015, 224: 1637–1652
70 Sedra S, Smith K C. Microelectronic Circuits. London: Oxford University Press, 2003
71 Ozkurt N, Savaci F A, Gunduzalp M. The circuit implementation of a wavelet function approximator. Analog Integr Circuits Process, 2002, 32: 171–175