Chaos, Solitons and Fractals 108 (2018) 15–24

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Investigation of dynamical behaviors of neurons driven by memristive synapse

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ARTICLE INFO

Article history:
Received 1 November 2017
Revised 11 January 2018
Accepted 11 January 2018
Available online 2 February 2018

Keywords:
Synapse
Electrical activity
Memristor
Bifurcation

ABSTRACT

Synapse is an important bridge for receiving and encoding signals, and the description for synapse current is critical for further signal processing. This paper investigates the dynamical characteristic in isolated neuron and chain neuronal networks with memristive autapse or synapses, respectively. Autapse plays important role in modulating the electrical activities, and thus the information encoding is enhanced. Within the improved neuron model, memristor is used to map the modulation of synapse current. Within an isolated new neuron model with memory, the modes in electrical activities can be controlled by the synapse current completely. Bifurcation analysis is carried out and mode transition is discussed. Furthermore, the modulation of synapse current on chain network is investigated, and the dependence of wave propagation on intensity of synapse is discussed. The diversity in synapse current can suppress the synchronization approach on the network.

1. Introduction

Accompanied by developing artificial intelligence, more researchers begin to investigate the potential mechanism of signal processing in brain [1–5]. Some neuroscientists discussed the retrieval methods, according to information encoded and transmitted in neural network [6,7], which is helpful to understand the dynamical behavior of the brain and application of artificial intelligence. Up to now, the investigation in brain science and artificial intelligence field has become attractive topics when it accounts for the mechanism about learning, memory, choosing and cognition in neuronal networks. Based on some mathematical and biological neuron models, memory effect and electromagnetic induction are considered [8–11]. It is important to discuss the connection topology between neurons, physical processing and encoding mechanism in electrical activities of neurons. The intelligent algorithm of like brain can help to create and improve the deep learning calculating and theory [12–14], the application technology like brain can design the intelligent controller and equipment [15,16]. Indeed, there is a capacity of storing up many information in single neuron and cooperation between neurons can enhance the ability of signal encoding with respect to detection of action potentials with singe-neuron sensitivity, the sensor composed of quantum defects within a diamond chip, detects mechanism of time-varying magnetic fields generated by action potentials [17]. Therefore, it is challengeable to design more effective neural network for rapid and exact signal processing. The formation of memory and learning mechanism have been discussed and the biological function of synapse can be understood [18]. Santiago et al. [19] claimed that memory stems from and is up to synapses, and it is possible that a large amount of synapse and various intensity of connection is to basic for leaning in brain. Carney et al. [20] summarized the principle of learning and memory in cell, and they confirmed that the varied intensity of synapses is enough to change the structure of neuronal network originally and ability of dealing with information, and short-term memory storage depend on time-length about increasing or decreasing intensity for synapses. In short, the synapse, the same as the neuron itself, plays an important role to understand dynamic characteristic and nature in brain.

The neuron in the nervous system is the basic functional unit for signal processing because the collecting, sorting, storing and transferring information can be accomplished by neurons. In the terms of information transition, synapse is a significant structure that permits a neuron (the presynaptic neuron) to pass an electrical or chemical signal to another neuron (the postsynaptic neuron) [21–25]. On the other hand, autapse (a specific synapse developed from auxiliary loop) can enhance self-adaption of neurons, and

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https://doi.org/10.1016/j.chaos.2018.01.017

thus appropriate modes in electrical activities can be selected [26–31] when autaptic modulation is triggered. The autapse is classified into two types: electrical, chemical way combined axon with dendrite [32–34]. In experimental way, autapse is found in substantia nigra, and the autaptic modulation on electrical activities is analyzed to confirm the biological function of autapse connection. So, excitability is adjusted to reproduce the electrical activity of neural behavior are detected by emulating theoretical neuron model [35,36] driven by autapse. For the neural basket cell, the autaptic modulation is considered on Hodgkin-Huxley model by applying time-delayed feedback to the soma of the itself, is proposed to detect the dynamical response and potential biological function of autapse connection [37]. Particularly, Qin et al. [38] confirmed that local distribution of autapses and appropriate parameter setting in autapses can induce stable formation of target waves,and break up of target waves can develop spiral waves in the network. Song et al. [39] confirmed the positive contribution of autaptic modulation on synchronization in a forward feedback network. Excitability modulation is important to trigger mode transition in electrical activities. As mentioned by the researchers [8], autaptic modulation and neurons contribute to the collective signal encoding, the astrocytes also have supportive and protective functions to neurons. Seri et al. [40] confirmed that a population of small electron-dense subgranular layer cells can be derived from the astrocytes, and probably behave as a transient precursor in the formation of new neurons. That is to say, astrocytes help to produce new neurons in the adult mammalian hippocampus. Tang et al. [41] constructed a minimal neuron-astrocyte network model by connecting a neurons chain and an astrocytes chain and the results found that calcium wave propagation in astrocytes determines the propagation of seizure-like discharges (SDs) in the connected neurons. Reactive astrocytes are proposed and it may provide a permissive substratum to support axonal regrowth after an injury to the CNS in recently studies [42,43].

Based on the neuron models, some researchers thought that neural circuits [44,45] can also be effective to understand the mechanism for signal processing. For example, the synchronization problems such as exponential stochastic, robust, have been investigated in neural networks with stochastic noise perturbations, mixed delay and uncertain parameters [46,47]. The spiking activities of neurons on 3D Morris-Lecar model is worthy of further investigating. Upadhyay et al. [48] discussed the dynamical synchronization, and took advantage of this model to interconnect by excitatory and inhibitory neurons with noisy electrical coupling synapse. Some researchers confirmed that the behavior of memristor is similar to those described by synapse [49,50]. In the electrical-biological term, the nonvolatile nature of memristor makes them an attractive candidate for the simulated synapses. Chain network is effective to describe the collective behaviors in a large number of neurons, for example, La Rosa et al. [51] observed the arising of a new slow regular rhythm along the chain of unidirectional coupled neurons whose individual dynamics is periodic spiking, and the transition from a irregular spiking-bursting regime to a regime with regular bursts is detected. Fortuna et al. [52] presented some appealing applications of Cellular Neural Networks (CNNs) to illustrate complex image, visual and spatio-temporal dynamics processing. Panahi et al. [53] suggested an effective way to describe epilepsy behavior based on chaotic artificial neural network.

Therefore, motivated by the above discusses, we will confirm that synapse with the memristor of characteristic can be employed to the neuron models. The electrical activity of neuron is detected by observing the time series of membrane potential and calculating bifurcation diagram for parameters. Development of spatiotemporal patterns, based on the two bidirectional coupling-neurons by the memristive synapses, will be discussed. That is, electromagnetic induction and radiation, injury in neuron [54] can cause disturbance and even attack on neuronal activities. Seriously, some nervous diseases can be induced due to the blocking in signal propagation and encoding in neuronal activities. Most of the presented neuron models emphasize the contribution from ion currents across the membrane potentials induced by exchange of charged ions. However, effect of electromagnetic induction and injury on neuron is missed. Indeed, both electromagnetic induction, radiation, blocking in ion channels-induced injury can cause imperfect on neurons, and the presented models should be improved to describe the damage effect. In a word, improved neuron model should consider the imperfect effect so that the mode transition, synchronization and pattern stability on neuronal network can be estimated in exact way.

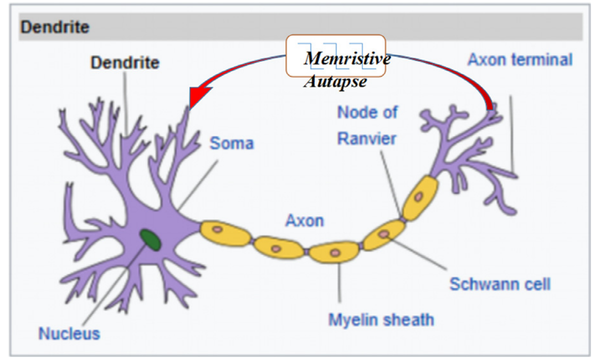

Fig. 1. Structure of a typical neuron with memristive autapse.

2. Model descriptions

A neural unit has three major factors, involving the dendrite to collect electrical signals, the nucleus and soma to encode information, and the axon to propagate electrical signals to dendrites of another cell. Synapse is just responsible for this coupling function between two neurons by linking the presynaptic axon terminal to the anterior membrane of dendrite. Autapse is a class of specific synapse which connects to its body via a close loop. As confirmed in Ref. [54], the formation of autapse could result from injury in axon and thus an auxiliary loop is developed to help signal propagation and self-adaption of neuron is enhanced. In most of previous works, the gain in autapse is fixed though the memory effect can be described by the variable of magnetic flux. The magnetic flux is time-varying when the electromagnetic filed is changed continuously. Inspired by the scheme in Refs. [55,56], magnetic-controlled gain in autapse is proposed to model the synapse current by using memristor coupling. In this way, a reduced diagram is plotted for a new neuronal model with a memristive autaptse connection, and a self-delayed feedback is triggered in Fig. 1.

Considering the dynamic state of Hopfield-type model, FitzHugh et al. [57] developed the FitzHugh–Nagumo model by using the Bonhoeffer-van der Pol model in 1961. It suggests that the oscillating variable x is also modulated by a damping function depended on quadratical nonlinear term x, and the dynamical equation is described by

$$\frac{d^2x}{dt^2} - \frac{1}{a}\left(1 - x^2\right)\frac{dx}{dt} + x = 0 \tag{1}$$

where $1/a$ is a positive constant, and $(1 - x^2)\ /\ a$ represents nonlinear function dependent on the variable x. For available dynamical analysis, an auxiliary variable y is used to approach a two-variable

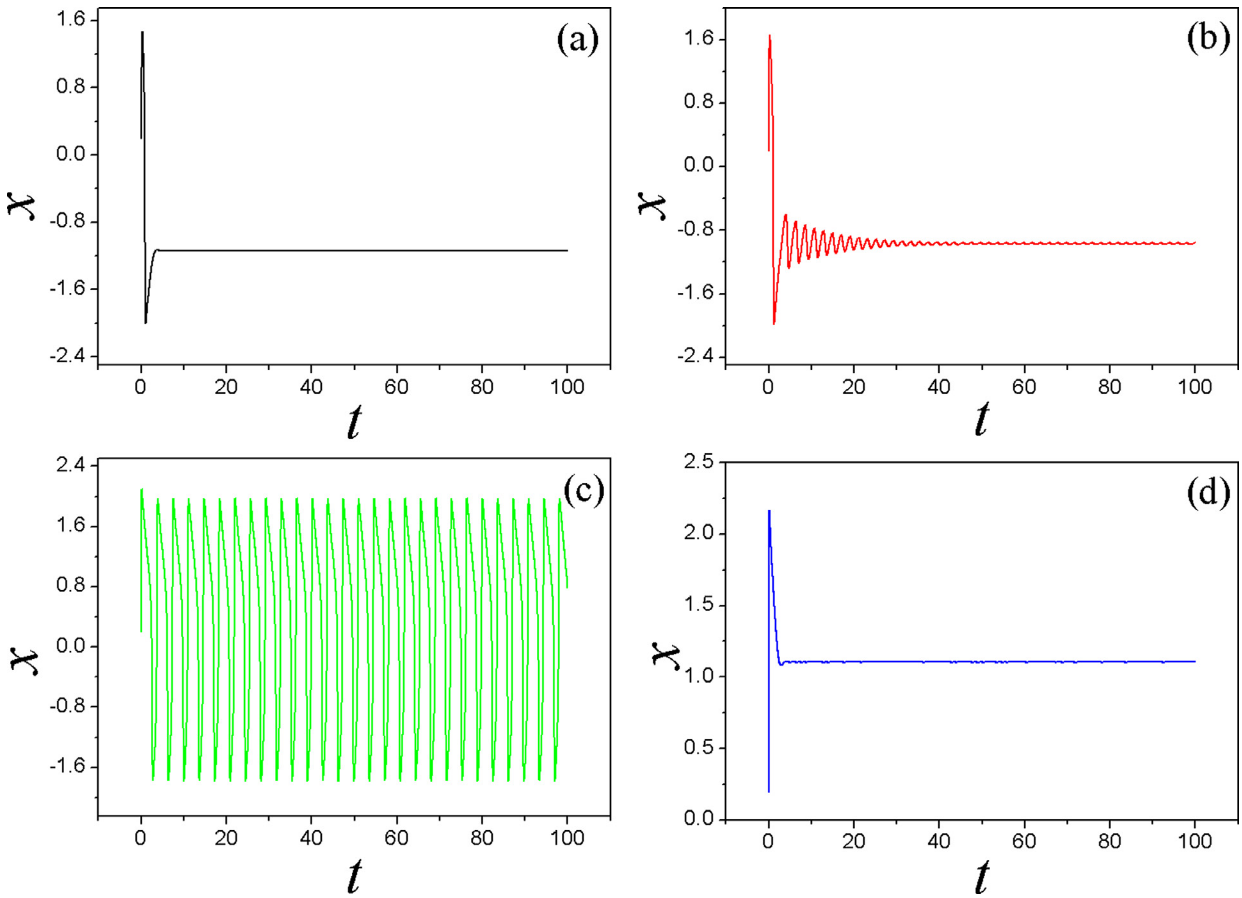

Fig. 2. Time series of membrane potential are calculated by applying different external forcing current(*DC*), for (a) $I_{ext}=0.1$; (b) $I_{ext}=0.31$; (c) $I_{ext}=1.3$; (d) $I_{ext}=1.6$; the parameters of system are selected as $a=0.1$, $b=0.8$, $c=0.7$.

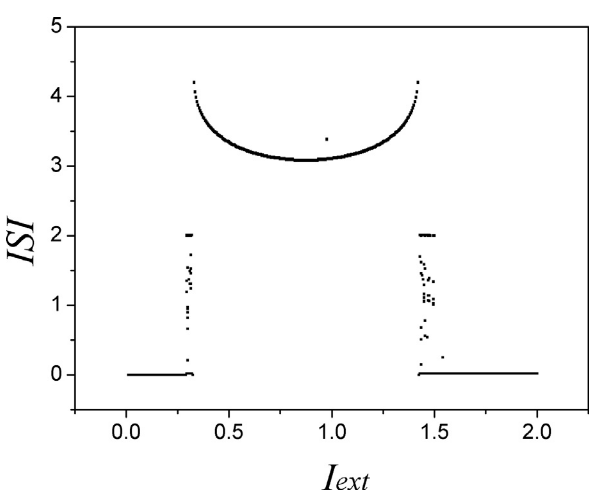

Fig. 3. Bifurcation diagram of the interspike interval for membrane potential vs. external forcing current I_{ext}. The parameters are set as $a=0.1$, $b=0.8$, $c=0.7$. Within the sampled time series for membrane potential, the peak value for membrane potential is recorded only when the membrane potential is beyond the values for the pre-adjacent and post-adjacent time.

dynamical equations shown as follows

$$y = x - \left(a\frac{dx}{dt} + \frac{x^3}{3}\right) \rightarrow \begin{cases} \frac{dx}{dt} = \frac{1}{a}(x - x^3/3 - y) \\ \frac{dy}{dt} = ax \end{cases} \tag{2}$$

where y can be thought as a variable associated with magnet flux because the second differential equation $dy/dt = ax$ presents similar physical law of electromagnetic induction when the first variable is used as membrane potential for the model. Furthermore, this model is improved to detect the essence of electrical activity and memory effect [58], it is redefined as follows

$$\begin{cases} \frac{dx}{dt} = \frac{1}{a}(x - y - \frac{x^3}{3} + I_{ext}) + I^{Msyn} \\ \frac{dy}{dt} = x - by + c \end{cases} \tag{3}$$

where x is the transmembrane potential, y represents the magnetic flux that was regarded as an appropriate substitute for the traditional medium term or current term in the background of vibration mechanism or biological science, respectively. Furthermore, memristive synapse is considered by adding memristive induction current I^{Msyn} on the neuron. The parameter b represents the feedback gain for electromagnetic field, and c is corresponding to a voltage threshold. I_{ext} is the external forcing current. The nonlinear term I^{Msyn} denotes the autapse or synapse current consisted of the magnetic flux and membrane potential. The time-varying electromagnetic field can be set up during the fluctuation of electrical activities in cells according the law of electromagnetic induction. In the perspective of biophysics, various electromagnetic fields can be discussed by using the magnetic flux φ if possible. As a result, a memristor is used to bridge the membrane potential and magnetic flux [55,56], thus the induction current can be approached. Memristor is a new device composed of complex nonlinearity, and it is often used for nonlinear circuits with memory effect. The nonlinear synapse current with memristor applied on isolated neuron is described by

$$I^{Msyn} = g\rho(y)[x(t) - x(t-\tau)];\ \rho(y) = \frac{dq(y)}{dy} = \alpha + 3\beta y^2 \tag{4}$$

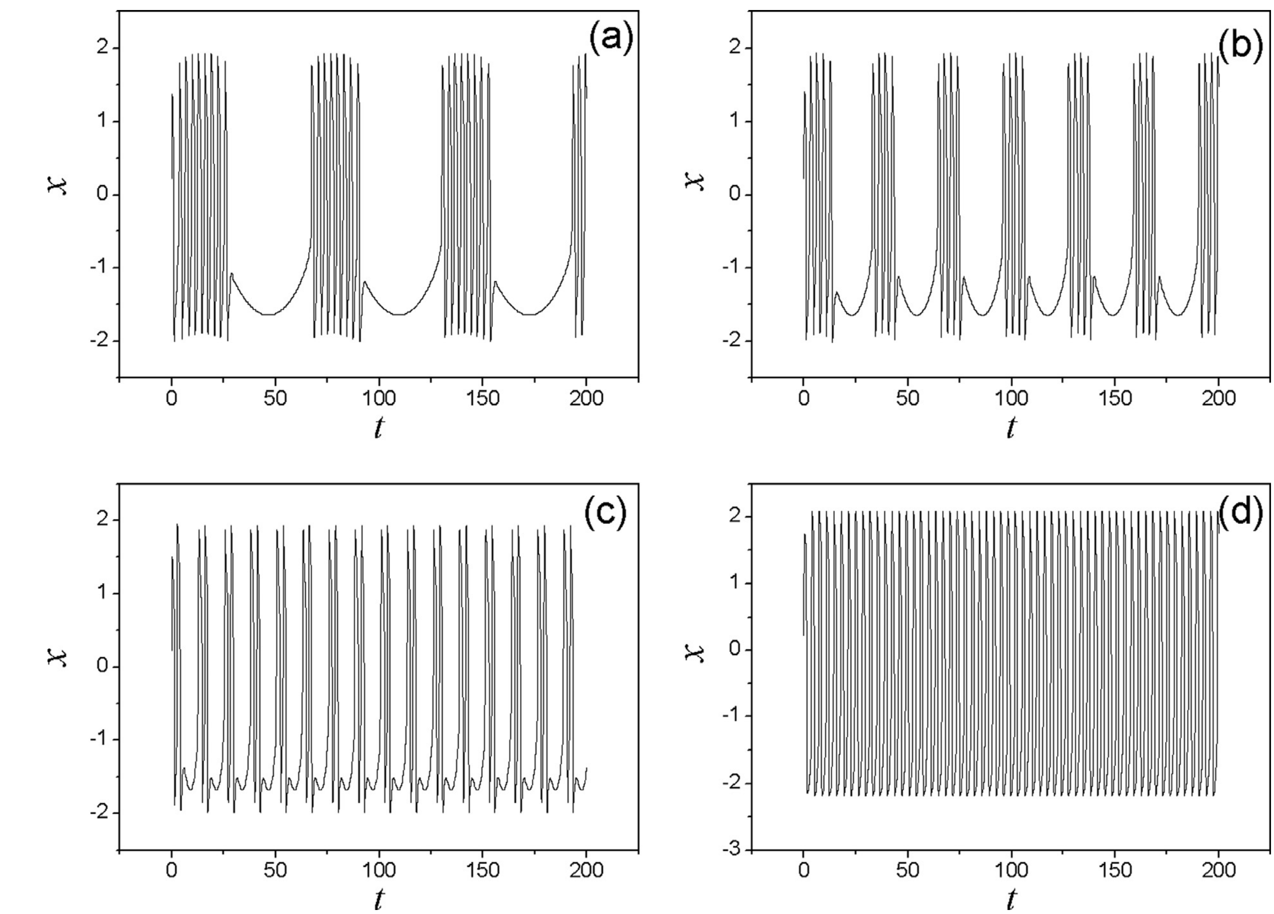

Fig. 4. The time series of membrane potential under amplitude $A = 1.0$ and different angle frequency, for (a)$\omega = 0.1$;(b)$\omega = 0.2$;(c)$\omega = 0.5$;(d)$\omega = 1.8$; the parameters of system are selected as $a = 0.1$, $b = 0.8$, $c = 0.7$.

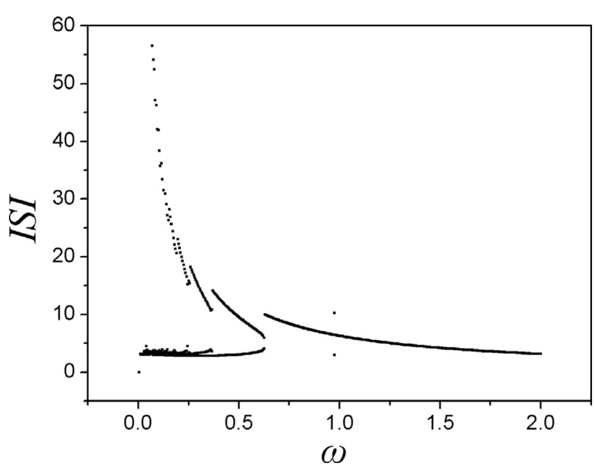

Fig. 5. Bifurcation diagram of the interspike interval for membrane potential vs. the gain ω, the parameters are set as $A = 1.0$, $a = 0.1$, $b = 0.8$, $c = 0.7$.

where the parameter τ denotes the time delay in the autapse with electric type. Furthermore, the synapse current between neurons in the chain network can be calculated by

$$I_i^{Msyn} = K \sum_{j=1}^{N} \rho(y_j) w_{ij}(x_j - x_i), \ \rho(y) = \frac{dq(y)}{dy} = \alpha + 3\beta y^2 \tag{5}$$

where $q(y)$ is the memristor constitutive relation, the parameters (α, β) are often selected as $\alpha = 0.2$, $\beta = 0.2$, and memristor can be used to replace some other electric devices in the well-known nonlinear circuits such as Chua circuit, Jerk circuits. By setting appropriate parameters, the memristor-coupled nonlinear circuit can generate chaotic state completely. Both g and K denote the memristive intensity. The subscript i, j denotes the node position in the network, and w_{ij} defines the connection state between two neurons. $w_{ij} = 1$ when two neurons on node (i) and (j) are connected, otherwise, $w_{ij} = 0$. The $\rho(y)$ term calculates the memductance of memristor. In the next section, numerical studies are carried out and the dynamical response of neurons modulated by memristive synapse will be discussed.

3. Numerical results and discussions

The electrical modes in neurons are much dependent on the excitability and external forcing can change the excitability of neurons. Bursting state is one of an extremely diverse general phenomenon in firing patterns in the central nervous system and spinal cord [59]. The neurons generally exhibit abundant dynamic behaviors such as quiescent, regular spiking, periodic, and chaotic bursting firing pattern. The numerical solution is approached by using the fourth Runge–Kutta algorithm with time step $h = 0.01$. Firstly, we investigate the dynamical response of isolate neuron when autapse is removed, and external stimulus is adjusted to trigger action potential. The initial values are selected as $(x_0, y_0) = (0.2, 0.01)$, the sampled membrane potentials for an isolated neuron are

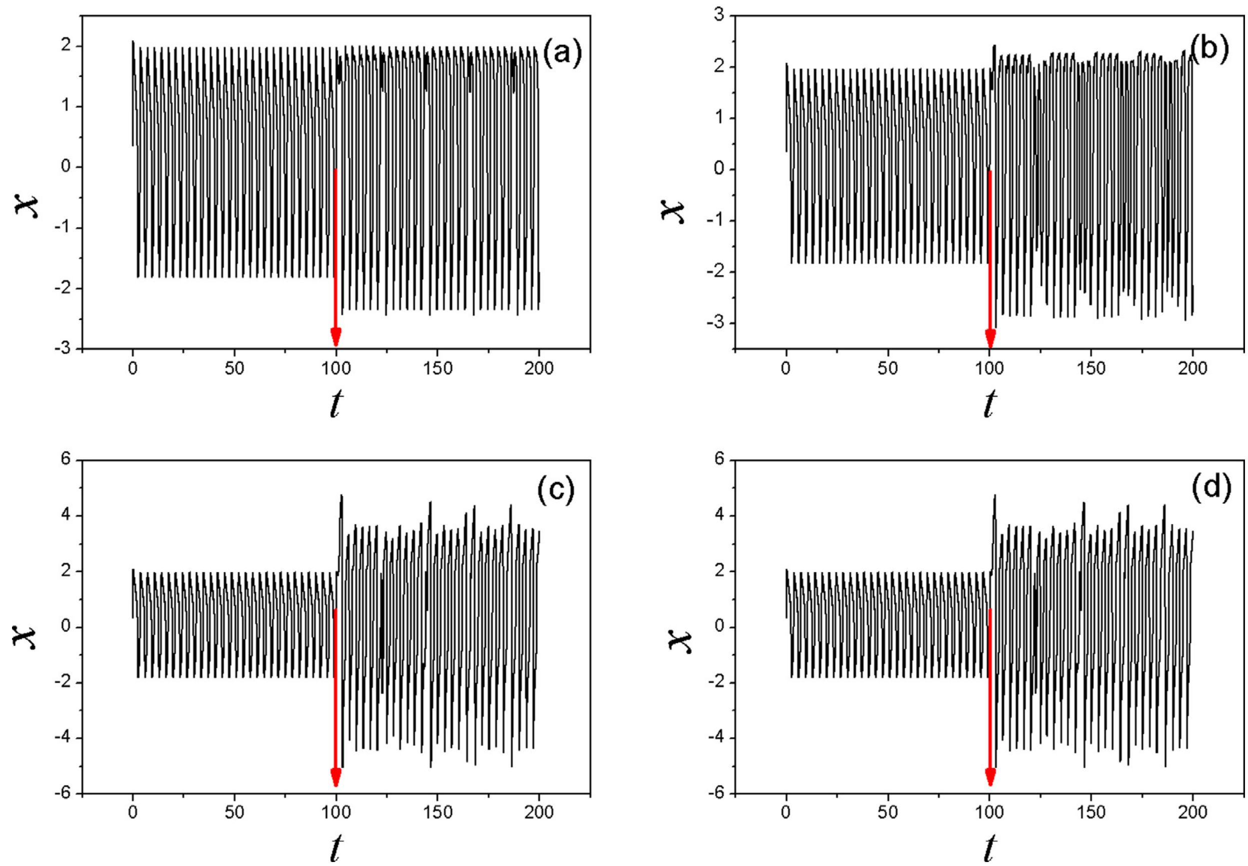

Fig. 6. Transition in electrical activities is plotted by setting different memristive intensities. The feedback gain is selected as $g = 1.0$, 2.0, 3.0, 5.0, time delay in the autapse is fixed at $\tau = 20$, external stimulus is selected as $I_{ext} = 1.3$ and synapse current is applied at $t = 100$ time units, the parameters are set as $a = 0.1$, $b = 0.8$, $c = 0.7$.

detected to observe the firing pattern in electrical activities by selecting appropriate forcing for I_{ext}, and the results are showed in Fig. 2.

It is found in Fig. 2 that the spiking, periodical and quiescent state can be observed by selecting appropriate external forcing current I_{ext}, which changes the excitability. Furthermore, the interspike interval(ISI) are calculated from sampled time series to detect the bifurcation vs. external forcing current I_{ext}, and the results are plotted in Fig. 3.

The bifurcation diagram in Fig. 3 confirms that mode transition can be triggered in the sampled time series for membrane potentials. Furthermore, the electrical activities in neuron are calculated by applying appropriate periodical stimulus, the amplitude and angular frequency are modulated to trigger different firing pattern and electrical activities. The results are showed in Figs. 4 and 5, respectively.

The sampled time series confirmed that bursting states can be induced by setting appropriate angle frequency in the periodical forcing current. The bifurcation analysis predicts the emergence of bursting, spiking and even quiescent state by applying appropriate angular frequency in the external stimulus. Next, the dynamics behavior is further discuss when autapse is considered. There are periodical and bursting state in this model while the appropriate external forcing current is selected. Indeed, it is important to consider the similar case when autaptic modulation is considered, and the biological function of autapse connection can be understood. To discern the effect of memristive synapse, the autapse driving is switched on from $t = 100$ units, numerical results are calculated by setting different gains g in the autapse, and the results are plotted as Fig. 6.

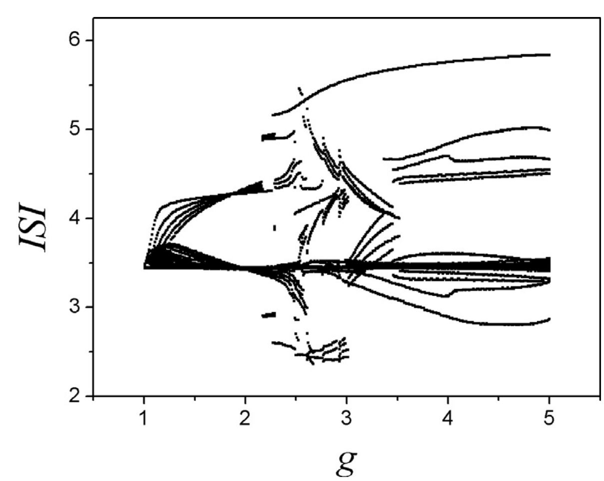

Fig. 7. Bifurcation diagram of the interspike interval of the neuron is calculated by applying different gains in autapse. Time delay in the autapse is fixed at $\tau = 20$.

The sampled time series show that distinct mode transition can be induced when autaptic modulation from autapse is activated, and the feedback gain in autapse contributes to the state selection greatly. Extensive bifurcation analysis is carried out by detecting the ISIs from the sampled time series for membrane potential when different gains in autapse are applied, and the results are plotted in Fig. 7.

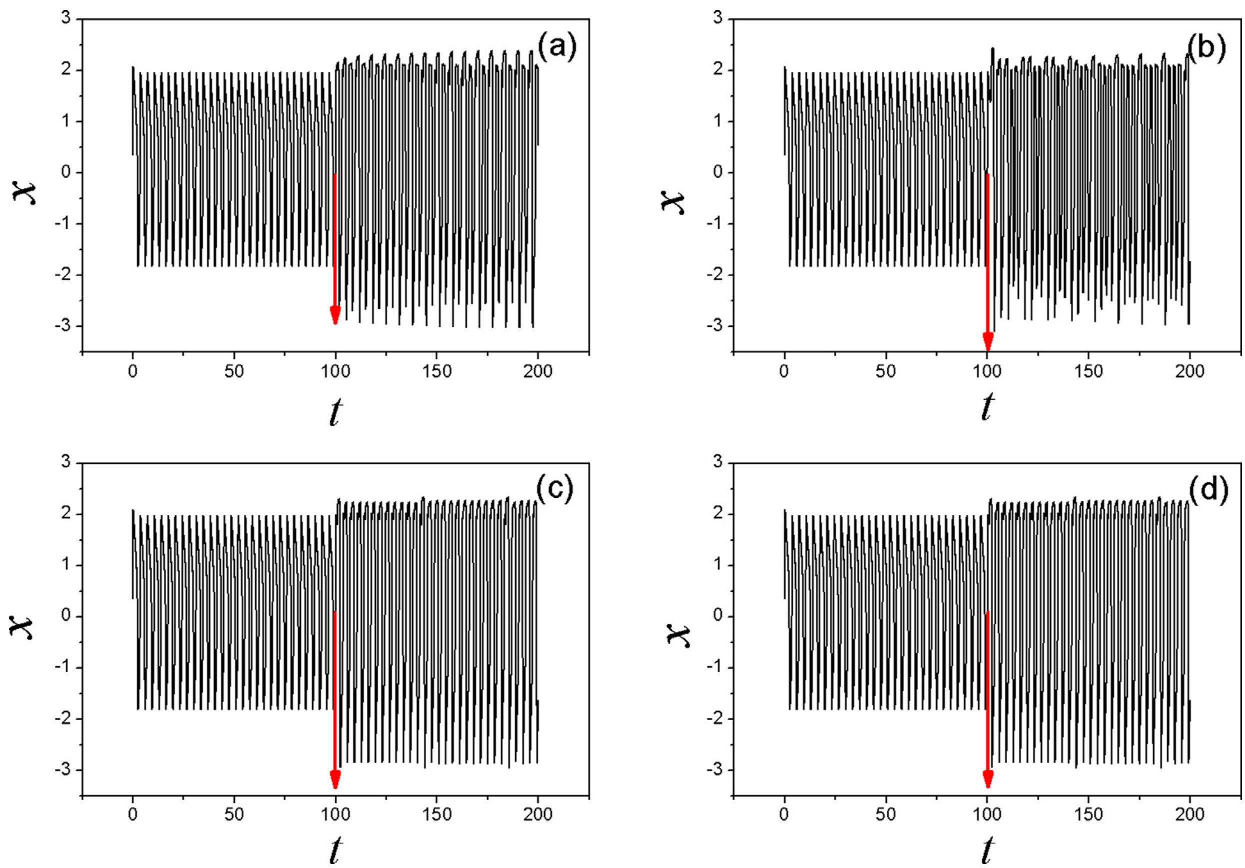

Fig. 8. Transition in electrical activities is plotted when autaptic current is triggered at $t = 100$ time units, the time delay in autapse is selected as $\tau = 5$, 10, 20, 40 time units, the memristive intensity $g = 2.0$ and external forcing current is applied as $I_{ext} = 1.3$, the parameters are set as $a = 0.1$, $b = 0.8$, $c = 0.7$.

The results in Figs. 6 and 7 found that autaptic modulation is effective to trigger mode transition in firing patterns. The self-synapse was first described as a synapse between the axon of a pyramidal cell and its own dendrites [60]. The autaptic modulation is regarded as a type of time-delayed feedback scheme, which is effective to control the dynamics of the nonlinear systems. The memristive autapse just applies time-varying induction current which is dependent on the magnetic flux on the neuron. Time delay describes the memory effect and contribution from the close loop for feedback. As a result, different time delays are considered in investigating the transition in electrical activities of neuron, and the results are illustrated in Fig. 8.

It is confirmed that the increase of time delay in the autapse can induce transition from spiking to aperiodic firing in the electrical activities when the gain in autapse is fixed. Furthermore, periodical stimulus is imposed to investigate the modulation from memristive autapse triggered at $t = 100$ time units, the results are shown in Fig. 9.

The sampled time series show distinct mode transition in the electrical activities, and the external periodical stimulus is encoded and modulated by memristive autapse greatly. With the increase of intensity of periodical forcing current, bursting firing is induced. The bifurcation analysis also confirmed the dependence of mode selection on gain in autapse when periodical forcing is also considered. Indeed, oscillator-like neuron models can describe the local kinetics of nervous system, a couple of improved neuron models have been proposed to understand the potential mechanism for mode selection and transition in electrical activities, for example, the autaptic modulation and astrocyte are coupled to neuron [8] and the biological function of autapse is discussed. Synapse connection bridges the neurons and signal propagation can be encoded effectively. In fact, field coupling between neurons could be another effective way to propagate signals and the electrical activities of neurons can be modulated, the potential mechanism could be that each cell can generate electromagnetic field and also controlled by electromagnetic field contributed by other neurons in the network. For relevant works and comments, readers can refer to our recent review in Refs. [56,61,62]. Finally, we discuss the wave propagation along chain network which local kinetics of neuron is described by neurons with memristive synapse, neurons are connected to the two adjacent neurons and no-flux boundary condition is used. The dynamical equations are defined as follows

$$\begin{cases} \frac{dx_i}{dt} = \frac{1}{a}(x_i - y_i - \frac{x_i^3}{3} + I_{ext}) + K\rho(y_i)(x_{i+1} + x_{i-1} - 2x_i) \\ \frac{dy_i}{dt} = x_i - by_i + c \end{cases} \tag{6}$$

The pattern evolution in the network is observed by setting different coupling intensities between neurons, the results are shown in Fig. 11. Random initial values are triggered as $x_0 = 0.2 + \text{random}\ (-0.1,\ 0.1)$, $y_0 = 0.01 + \text{random}\ (-0.1,\ 0.1)$

When the initial values are selected for neurons in random, each neuron develops electrical activities and no distinct wave propagation can be observed before activating the synapse coupling between neurons. It is found that wave is propagated along the network and the wave profiles become sparse with the increase of coupling intensity for memristive synapse because setting higher coupling intensity can enhance the wave and pulse propagation with higher velocity along the network. Complete synchronization can be approached on network composed of nonlinear oscillators between identical nodes when coupling intensity is be-

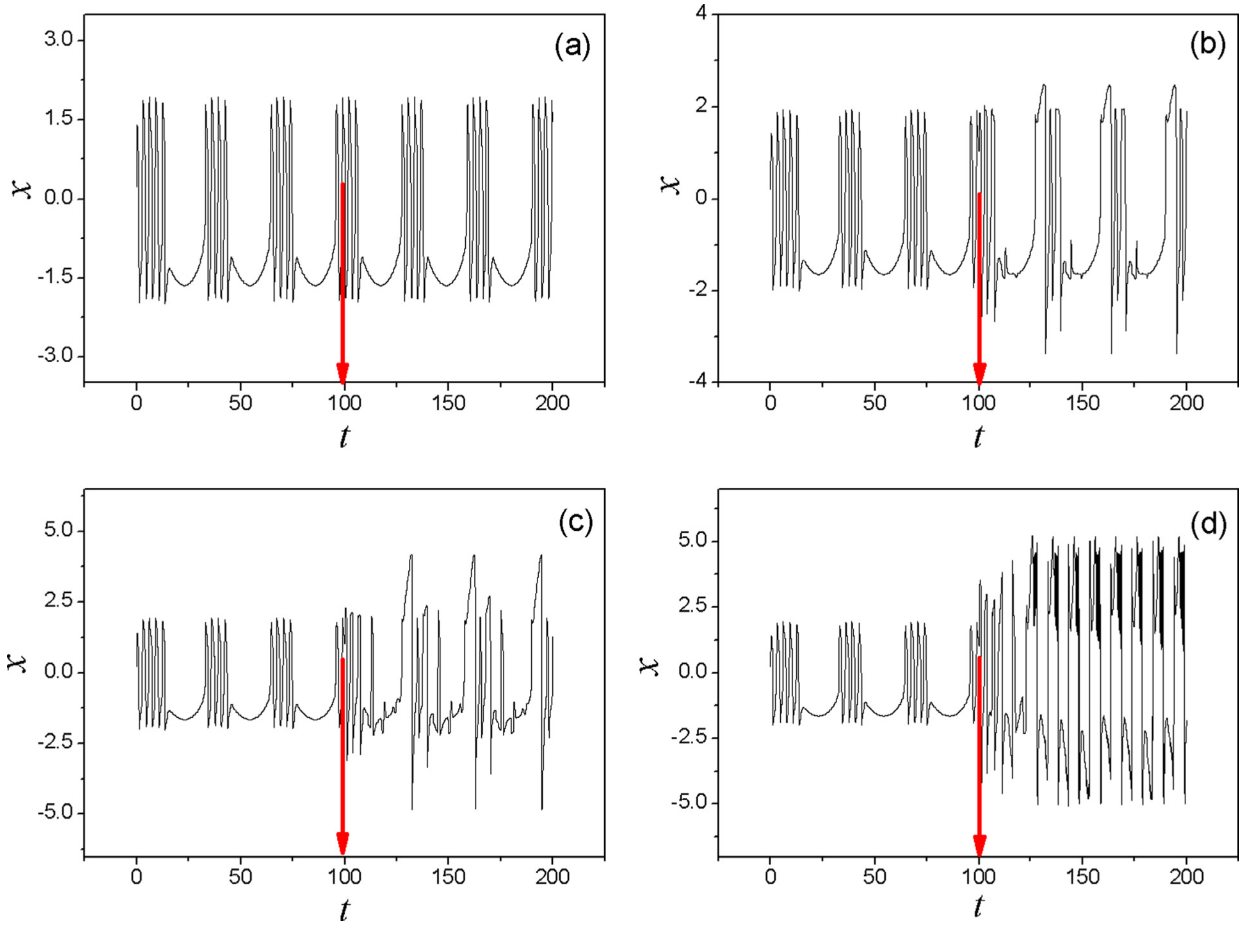

Fig. 9. Sampled time series are plotted when different memristive intensities are selected as $g = 0.0$, 2.0, 3.0, 6 time units, the external forcing current is selected as $I_{ext} = \sin 0.2t$, the parameters are set as $a = 0.1$, $b = 0.8$, $c = 0.7$, $\tau = 5$.

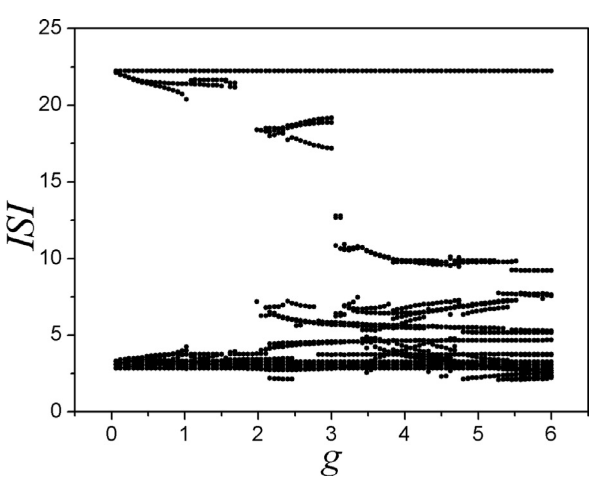

Fig. 10. Bifurcation diagram of the interspike interval of the neuron with a memristive autapse under the different intensities. Time delay in autapse is fixed at $\tau = 5$ and external stimulus is applied as $I_{ext} = \sin 0.2t$.

yond threshold, and distinct ordered state is developed to suppress wave propagation. The results in Fig. 11 found the wave propagation and the mechanism could be associated with memory effect of synapse. As a result, each neuron is modulated with different intensities because the memristor is endowed with different memductance $\rho(y)$. To further discern the synchronization stability, a statistical synchronization factor [38,56] is calculated according the mean field theory.

$$F = \frac{1}{N}\sum_{i=1}^{N} x_i, \quad R = \frac{< F^2 > - < F >^2}{\sum_{i=1}^{N}[< x_i^2 > - < x_i >^2]/N}, \tag{7}$$

Where the subscript i indicates the node position of the network, N is the number of nodes, the $<^*>$ symbol denotes the average calculation over time. The higher synchronization factor means that network is enhanced to reach perfect synchronization. For pattern selection, the smaller the factor of synchronization indicates possible occurrence of ordered spatial pattern in the network. In Fig. 12, the distribution for synchronization factor is calculated by changing the coupling intensity.

As well known, the increase of coupling intensity for coupled oscillators can enhance the synchronization. For identical oscillators embedded into the network, enough coupling intensity can drive the network to reach complete synchronization and the network will become homogeneous state. The results in Fig. 12 confirm that the synchronization factor is decreased with increasing the intensity of memristive synapse. As a result, the synchronization on the network becomes more difficult even when larger coupling intensity in the synapse is applied. In fact, the potential mechanism could be that each neuron is modulated by different synapse current because of diversity in $K\rho(y)$ and asymmetric coupling is triggered in the network. Furthermore, we also discussed the case when all nodes are selected the same initial values (0.2, 0.01), and the developed patterns are plotted in Fig. 13.

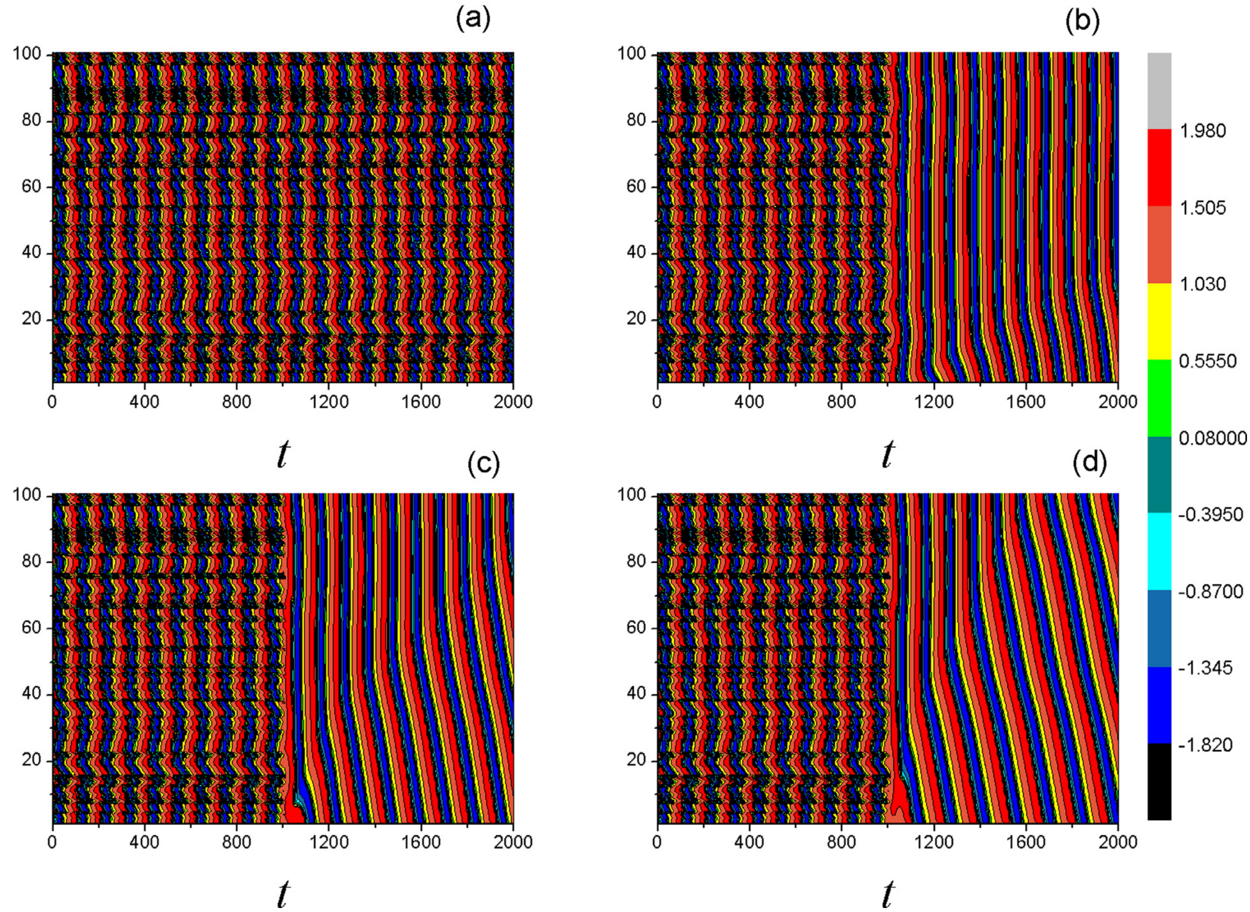

Fig. 11. Developed spatiotemporal pattern is plotted under different memristive intensities K, at $I_{ext}=1.3$, $\alpha=0.2$, $\beta=0.2$, (a)$K=0.0$; (b)$K=0.1$; (c)$K=0.5$; (d)$K=1.0$. The memristive synapse coupling is activated from $t=1000$ time units. The snapshots are shown color scale and random initial values are used for the network.

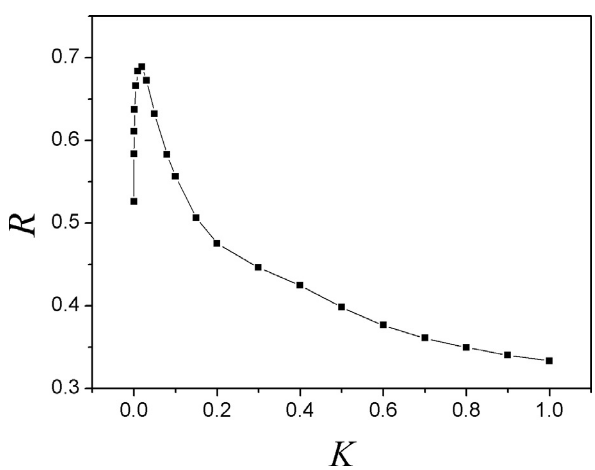

Fig. 12. Distribution for synchronization factor is plotted by setting different memristor intensities K.

It is found that the network shows the same oscillating behaviors before the memristive synapse is activated when all nodes are triggered by the same initials. Furthermore, pulse still can be induced to regulate all neurons when memristive synapse coupling begins to work, and asymmetric coupling is induced to generate homogeneity in the network. As a result, continuous pulse will emit from the homogeneity area and the network will be modulated greatly.

In a summary, different synchronization phenomena are observed in the network when neurons are connected via memristive synapses. The memristive synapse can modulate the electrical activities of neurons and stable pulses can be triggered along the network. The potential mechanism is that diversity in memristive synapse modulation can induce homogeneity in the network, and pacing-like pulses can regulate the network completely.

Finally, we would like to give some suggestions for the relevant topics. Synapse plasticity is helpful to enhance self-adaption in encoding information. It is known that electromagnetic radiation can impose distinct impact on biological system and nervous system. Memristive synapse suggests time-varying synapse coupling with appropriate intensity, and it is worthy of investigating the robustness to external electromagnetic radiation when neurons are exposed to electromagnetic field. As mentioned in Refs. [10,11,63–66], it is thought that electromagnetic field can change the magnetic flux across the membrane and thus the electrical activities can be modulated by applying induction current. Therefore, it is interesting to further discuss this problem when memristive synapse is considered, maybe, the involvement of memristive synapse can suppress the noise effect and induce ordered waves to enhance the spatial regularity in the network. Also, some suggestions can be found in the review [62,67]. Besides the contribution in Refs. [44,45], which neural circuits are designed to consider the verification of neuronal activities in experimental way, it is worthy of further considering the synchronization and consensus of chaotic circuits [68–70] composed of memristors. Researchers can extend this study on analog or digital circuits, and output response in Joseph-

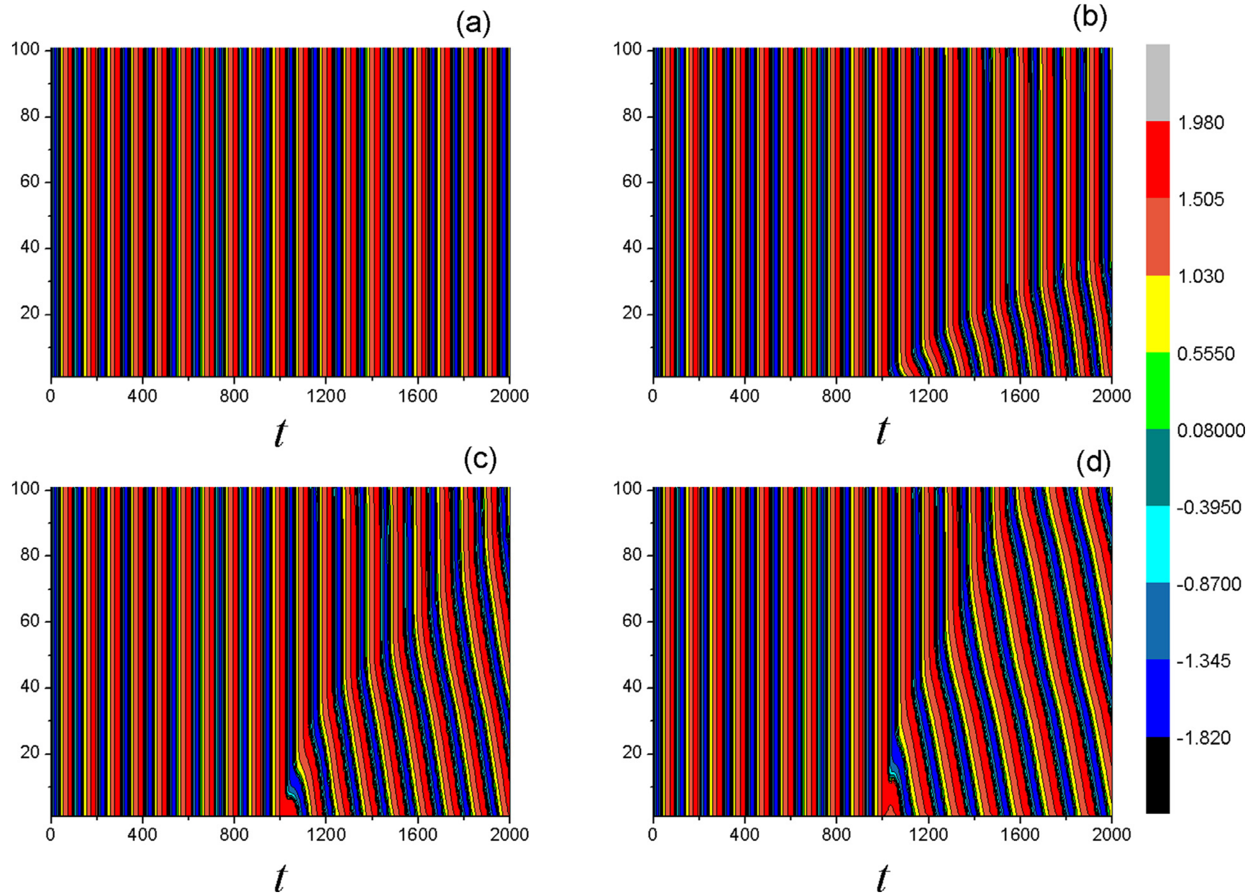

Fig. 13. Developed spatiotemporal pattern is plotted under different memristive intensities K, at $I_{ext} = 1.3$, $\alpha = 0.2$, $\beta = 0.2$, (a)$K = 0.0$; (b)$K = 0.1$; (c)$K = 0.5$; (d)$K = 1.0$. The memristive synapse coupling is activated from $t = 1000$ time units. The snapshots are shown color scale and same initial value (0.2, 0.01) is used for each node of the network.

son Junction coupled- memristor can be further investigated to design reliable intelligent circuits and signal processing.

4. Conclusions

Synapse plays important role in signal encoding and propagation between neurons. In this paper, an improved neuron model is presented by using memristive synapse, which the synapse coupling is replaced by a memristor and neurons are bridged for signal exchange. When the synapse with memory is activated, the electrical activities of neuron can be modulated to induce mode transition. When chain network is designed to investigate the collective responses of coupled neurons with memristive synapse connection, the complete synchronization becomes more difficult while regular patterns are induced by continuous pulses. It is thought that the formation mechanism for stable wave propagation could be associated with local homogeneity induced by diversity in synapse. To control the collective behaviors of neuronal activities completely, maybe, the memory effect of synapse should be suppressed.

Acknowledgement

This project is supported by National Natural Science Foundation of China under Grants. 11765011. We also give great thanks to professor J Ma(associate editor for Nonlinear Dynamics) for his careful discussion and editing.

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