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Multiple modes of electrical activities in a new neuron model under electromagnetic radiation

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ABSTRACT

The three-variable Hindmarsh–Rose model is improved to describe the dynamical behaviors of neuronal activities with electromagnetic induction being considered, and the mode transition of electrical activities in neuron are detected when external electromagnetic radiation is imposed on the neuron. The improved neuron model holds more bifurcation parameters and the mode of electric activities can be selected in larger parameter region. It is found that the electromagnetic radiation can excite quiescent neuron but also can suppress the electrical activities in neuron as well. Particularly, it is important to find that multiple modes of electrical activities can emerge alternatively, and these results are consistent with biological experiments.

1. Introduction

The neuronal system is made up of a large number of neurons, and signals are propagated between neurons under complex connection types. The dynamical behavior of electrical activities in neuron and neuronal network has been extensively investigated. For an isolate neuron, its electrical activities can show several of modes such as quiescent, spiking, bursting even chaotic states by applying appropriate external forcing current. Based on the original Hodgkin–Huxley neuron model [1], a variety of simplified neuron modes [2–5] have been established for theoretical and numerical investigation. It is believed that the membrane potential of neuron depends on the changes of transmembrane current, on/off of ion channels and even the regulation induced by astrocyte [6,7]. Based on mean field and properties of nonlinear oscillator, most of the neuron models can describe the dynamical properties in electrical activities. Indeed, the dimensionless Hindmarsh–Rose neuron model is reliable and available for bifurcation analysis [8,9] thus the mode transition in electric activities could be understood. Some researchers argued that more bifurcation parameters should be introduced into the three-variable neuron model so that bifurcation behaviors could be extensively investigated. For example, Refs. [10,11] presented a four-variable Hindmarsh–Rose neuron model by including more controllable bifurcation parameters, and Refs. [12–14] designed a neuron model driven by autapse thus the self-adaption to external forcing could be considered by adding two parameters (time delay and the feedback gain) in the autapse [15]. Gu et al. [16] set up a four-variable biological neuronal model to discern bifurcation behaviors induced by different ion currents. The process of metabolism is often associated with the electrical activities in neuron, and information transition and energy coding should be considered [17–19] during the signal processing and communication. Inspired by Refs. [20], which defined a statistical Hamilton energy by using Helmholtz theorem, the author of this paper confirmed that the mode in electrical activity in neuron is also associated with the energy release [21], for example, the Hamilton energy can be decreased greatly when neuron is under bursting and chaotic states, and it may give some guidance to understand the emergence mechanism for epilepsy. The potential mechanism could be that bursting synchronization induced epilepsy makes energy release explosively. Indeed, the electrical activities in neuron are also dependent on conductance in channels that channels blocking [22] can change the electrical modes of membrane potential for neurons. In fact, it is important to investigate the development and transition of collective behaviors of neurons by setting up different spatial networks [23,24], for example, the pattern selection and change of collective behaviors of neuronal network are changed by blocking [25,26] in ion channels embedded in the membrane of neurons. However, most of the neuronal models should be improved to consider more possible factors such as parameters setting, external forcing, physical evidence and description.

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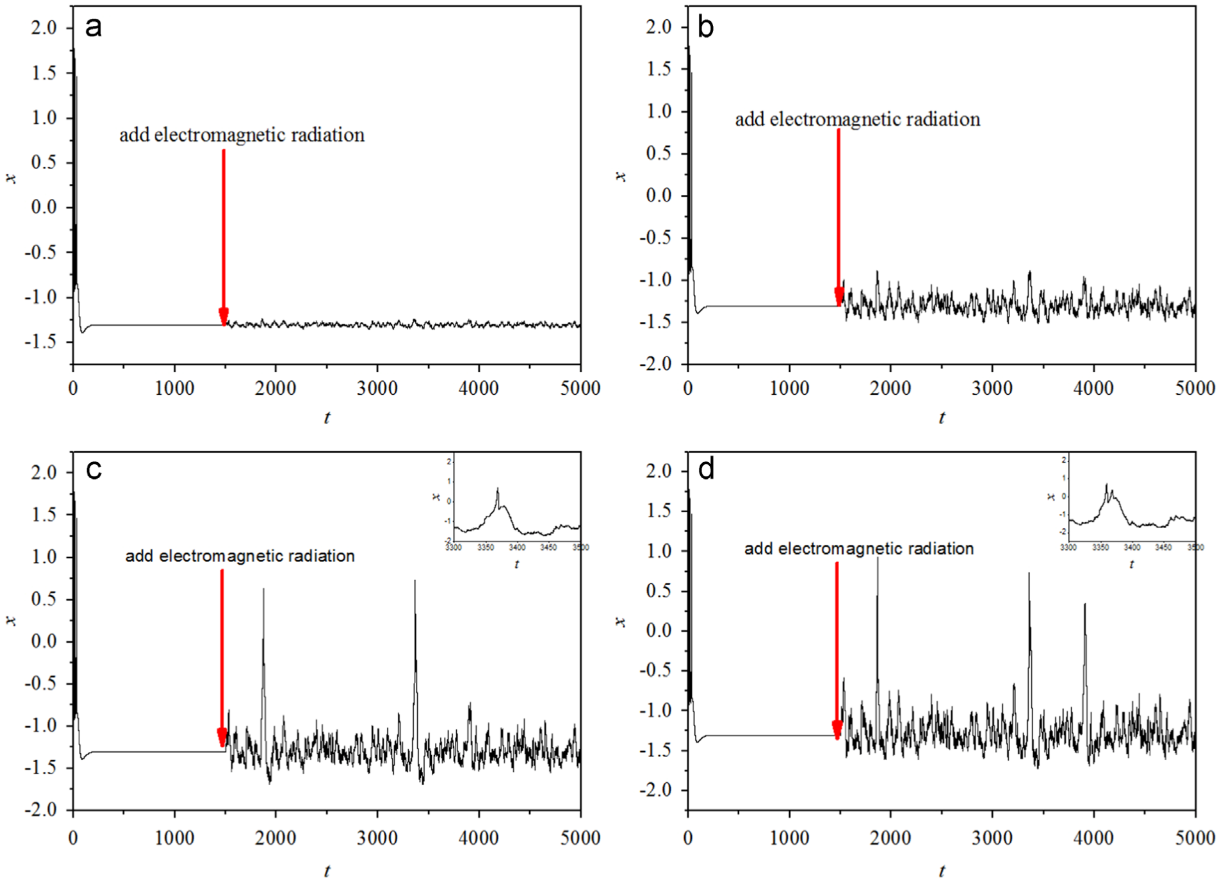

Fig. 1. The transition of electrical activities in an isolate neuron when electrical field radiation is switched on $t=1500$ time units, and external forcing current $I_{\mathrm{ext}}=0.8$. For intensity (a) $D=0.1$, (b) $D=0.5$, (c) $D=0.7$, (d) $D=0.9$.

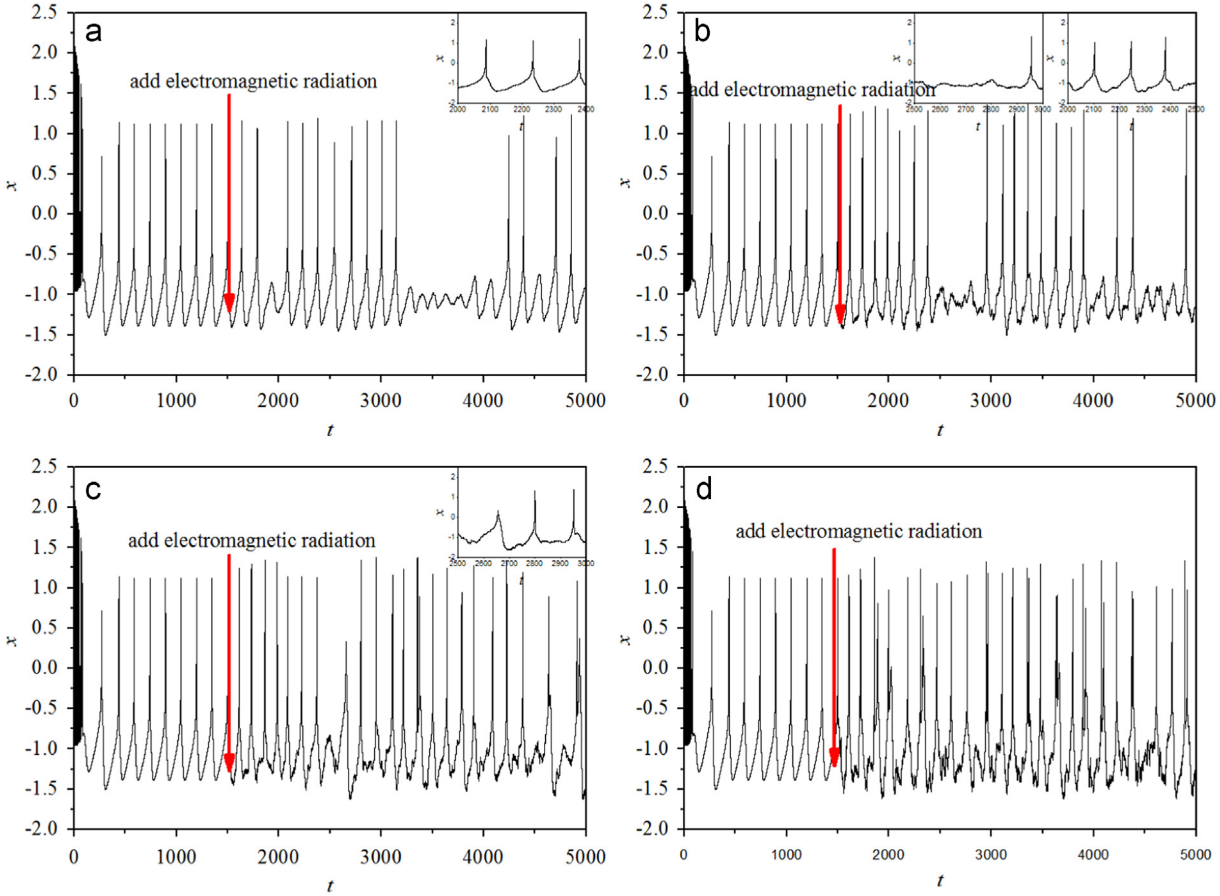

Fig. 2. The transition of electrical activities in an isolate neuron when electrical field radiation is switched on $t=1500$ time units, and external forcing current $I_{\mathrm{ext}}=1.84$. For intensity (a) $D=0.1$, (b) $D=0.3$, (c) $D=0.4$, (d) $D=0.7$.

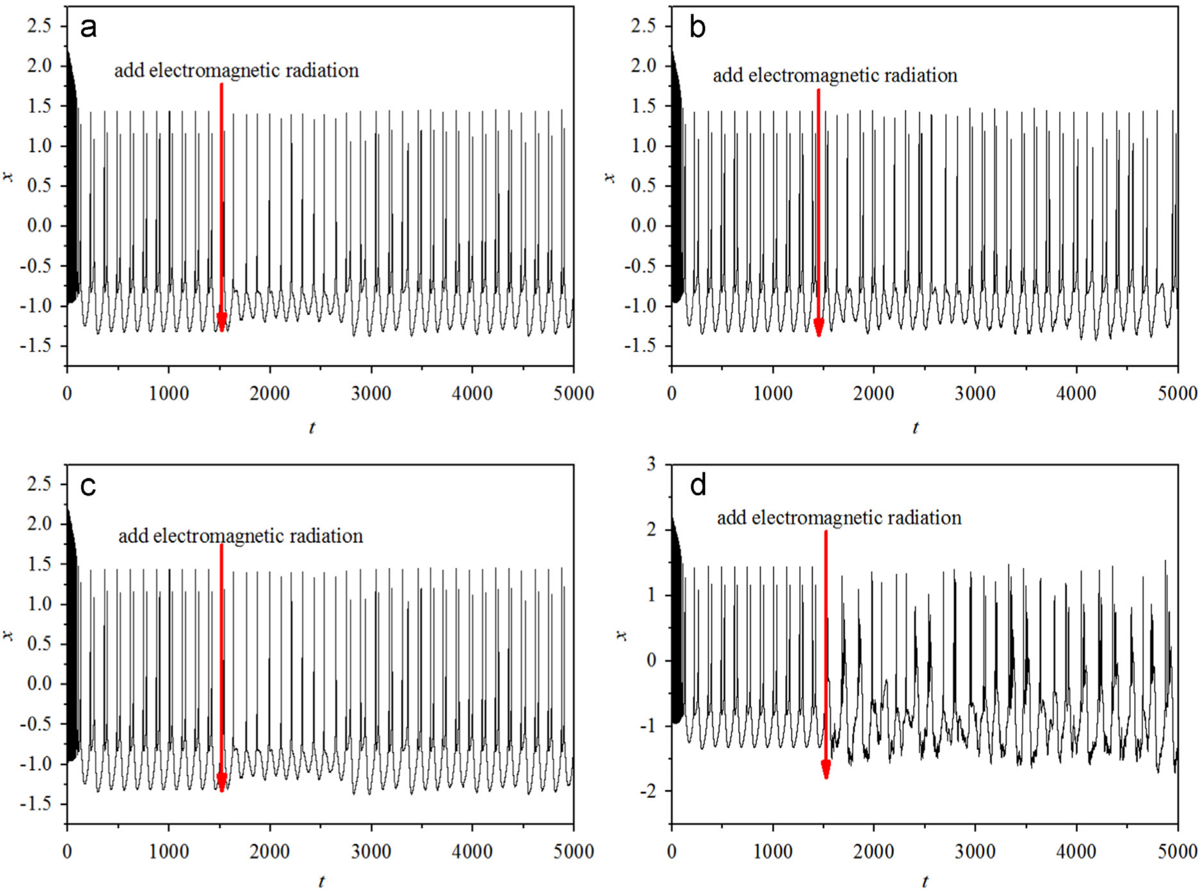

Fig. 3. The transition of electrical activities in an isolate neuron when electrical field radiation is switched on $t=1500$ time units, and external forcing current $I_{\text{ext}}=2.6$. For intensity (a) $D=0.1$, (b) $D=0.2$, (c) $D=0.4$, (d) $D=0.9$.

Based on the previous neuronal model, the effect of external forcing is often mapped into additive transmembrane current, which changes the dynamical behaviors of membrane potentials for neurons. For neuron model with ion channel being considered, the conductance for channels is changed to describe the external invasion such as channel poisoning. Within these neuron models, the external forcing just induces determinist electric mode under fixed parameter or external forcing. When neuron is exposed to electromagnetic radiation, some authors argued that the effect of radiation could be described by an equivalent current in neuronal loop [27] thus the electrical activities could be detected. To our knowledge, the fluctuation in membrane potential could induce the change of electromagnetic field or the distribution of ion concentration in cells, that is to say, the electromagnetic induction should be considered in neuron or cell. Yin et al. [28,29] confirmed that neuron could show distinct Spike-frequency adaptation when the neuron is modulated by extracellular electric fields. Akiyama et al. [30] showed that CA1 pyramidal neurons indeed show the characteristic polarization in response to DC fields, and investigated the mechanism underlying the profiles by using optical imaging and patch-clamp recordings. Clinical effects of transcranial electrical stimulation with weak currents are remarkable considering the low amplitude of the electric fields acting on the brain which is composed of ten billions of neuron. It is of great importance for the rational design of noninvasive electrotherapeutic strategies discern the processes by which small currents affect ongoing brain activity, and to determine the relevance of endogenous fields Reato et al. [31] found that carbachol-induced gamma oscillations (25–35 Hz) in rat hippocampal slices have an inherent rate-limiting dynamic and timing precision that govern susceptibility to low-frequency weak electric fields (<50 Hz; <10 V/m).

It is believed that bifurcation analysis [32–36] could be effective to understand the transition of modes in electric activities and stability. Particularly, the experimental works presented by Gu et al. [16,35–38] and further bifurcation analysis threw light on understanding the mode transition of electric activities of neurons. Indeed, the signals and information could be recorded by magnetic field. As a result, it is important to improve the previous neuron models so that the effect of magnetic field and even the electromagnetic radiation could be estimated if possible. In this paper, we presented an improved neuron model that different modes in electrical activities could be observed alternatively under appropriate external electromagnet radiation or forcing.

2. Model, results and discussion

The mathematical Hindmarsh–Rose model can produce main dynamical properties in electrical activities for neuron. As mentioned above, the effect of electro-magnetic induction should be considered during the fluctuation in membrane potentials of neurons. In fact, the magnet flux is often used to detect the change of electromagnet field, and the improved model is defined as follows:

$$\begin{cases} \dot{x}=y-ax^3+bx^2-z+I_{ext}-k_1W(\varphi)x \\ \dot{y}=c-dx^2-y \\ \dot{z}=r[s(x+1.6)-z] \\ \dot{\varphi}=kx-k_2\varphi+\varphi_{ext} \end{cases} \tag{1}$$

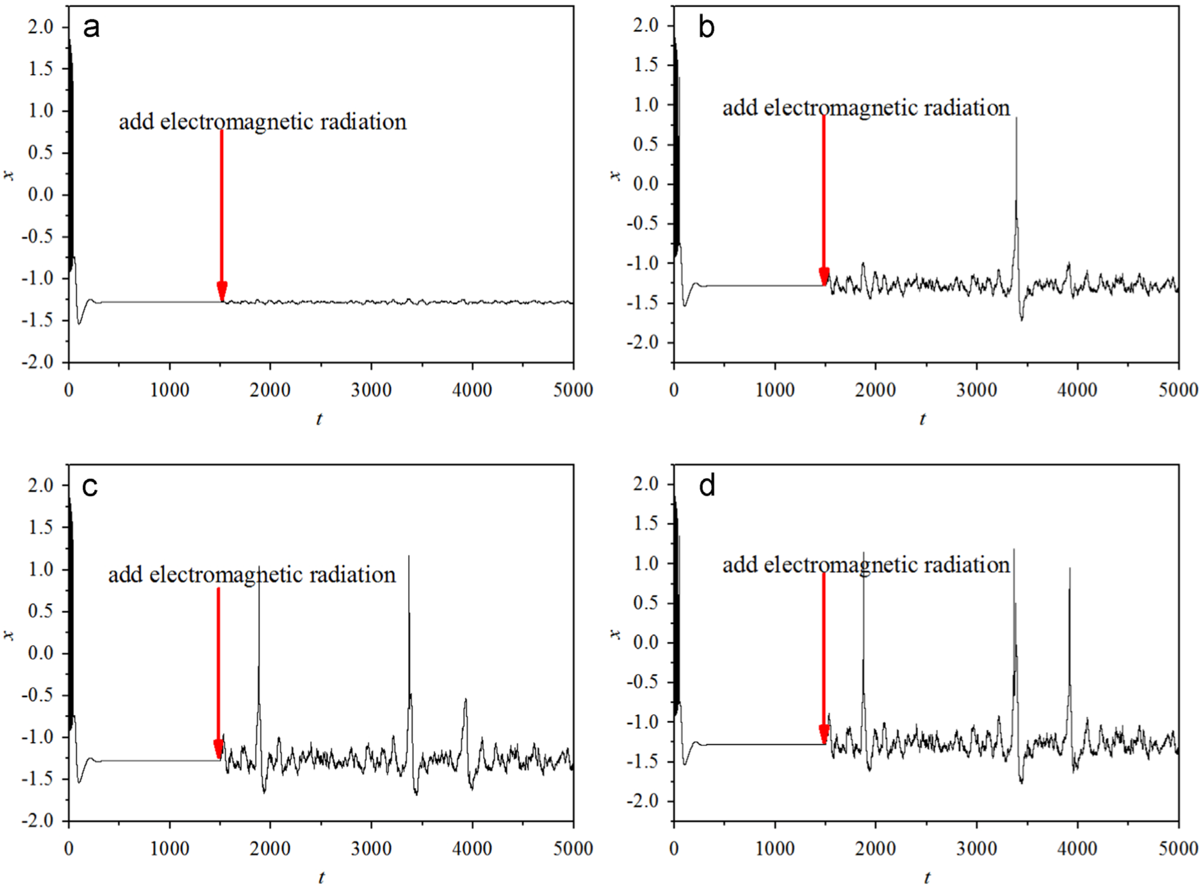

Fig. 4. The transition of electrical activities in an isolate neuron when electrical field radiation is switched on $t=1500$ time units, and external forcing current $I_{\text{ext}}=1.1$. For intensity (a) $D=0.1$, (b) $D=0.6$, (c) $D=0.8$, (d) $D=0.9$.

where x, y, z, φ describes the membrane potential, slow current associated with recovery variable, adaption current, magnetic flux across the membrane of neuron (or cell), respectively. I_{ext} is external forcing current and the term $k_1W(\varphi)x$ defines the feedback current on membrane potential when magnet flux is changed, and k_1 is the feedback gain. The dependence of electric charge on magnet flux is defined by the memory-conductance as follows:

$$W(\varphi)=\frac{dq(\varphi)}{d\varphi}=\alpha+3\beta\varphi^2 \tag{2}$$

The physical significance for the term $W(\varphi)x$ could be described as follows:

$$i=\frac{dq(\varphi)}{dt}=\frac{dq(\varphi)}{d\varphi}\frac{d\varphi}{dt}=W(\varphi)\frac{d\varphi}{dt}=W(\varphi)V=k_1W(\varphi)x \tag{3}$$

where the variable V denotes the induced electromotive force, which holds a same physical unit, and parameter k_1 is the feedback gain. The term kx, $k_2\varphi$ in Eq. (1) describes the membrane potential-induced changes on magnet flux and leakage of magnet flux, respectively. The term φ_{ext} is external field or electromagnet radiation-induced magnet flux on the membrane. The parameters are selected as $a=1$, $b=3$, $c=1$, $d=5$, $r=0.006$, $s=4$ in the numerical studies. For simplicity, the effect of external magnet field could be described by Gaussian white type of noise

$$\varphi_{ext}=\xi(t),\quad <\xi(t)>=0,\quad <\xi(t)\xi(t')>=2D\delta(t-t') \tag{4}$$

where D is the noise intensity, and $\delta(^*)$ is Dirac-δ function. In the numerical studies, parameters are set as $\alpha=0.1$, $\beta=0.02$, $k_1=1.0$, $k_2=0.5$, $k=0.9$, and fourth order Runge–Kutta algorithm is used under time step $h=0.01$. Compared with the previous version, the improved model holds more bifurcation parameters.

At first, the external forcing current is selected by $I_{\text{ext}}=0.8$, and then different external electromagnet radiation-induced magnet flux is imposed with different intensities. In Fig. 1, the time series for membrane potentials under different intensities D are calculated. To discern the effect to external field, the neuron develops without external field driving before $t=1500$ time units.

The results in Fig. 1 confirmed that the quiescent neuron can be excited from quiescent state, and even can develop into bursting state with increasing the intensity of external radiation field. Furthermore, the external forcing current is increased to $I_{\text{ext}}=1.84$, which is effective to induce spiking state when no external radiation field is considered, and these results are shown in Fig. 2.

It is found in Fig. 2 that the electrical activities could be suppressed within certain transient period, for example, the spiking state is decreased greatly at $t=3500$ time units. Multiple electrical modes in electrical activities could be observed with increasing the intensity of external radiation field. By further increasing the external forcing current thus bursting state could be induced. For example, external forcing current is set as $I_{\text{ext}}=2.6$ to develop continuous bursting state, and then the external radiation field is imposed on the neuron, and the results are calculated in Fig. 3.

Indeed, the initial bursting state is switched between spiking and bursting states alternatively when the external radiation field is selected by appropriate intensity. These results confirm that the improved model can generate a variety of response modes to external forcing because more parameters are included into the model. This model explains that neuron can select appropriate

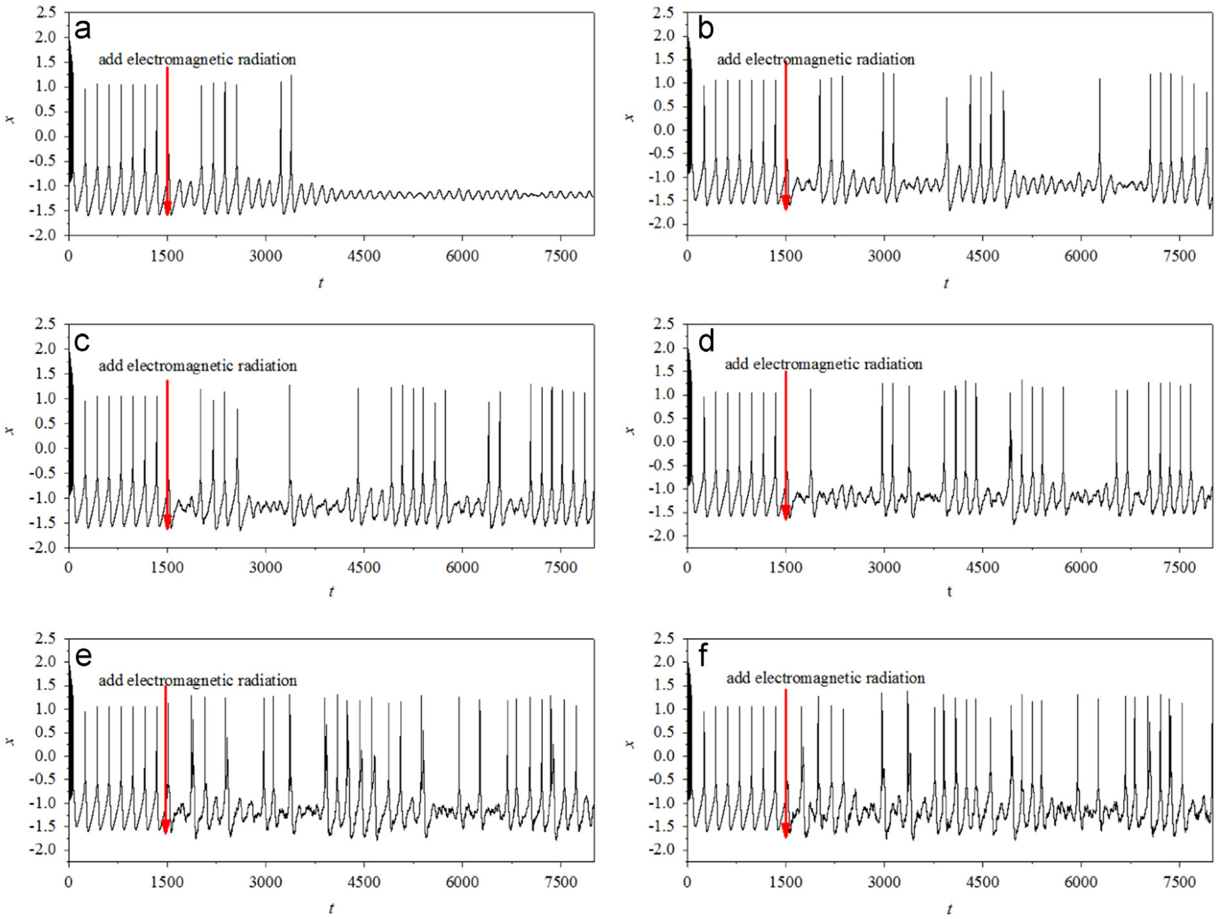

Fig. 5. The transition of electrical activities in an isolate neuron when electrical field radiation is switched on $t=1500$ time units, and external forcing current $I_{\text{ext}}=1.51$. For intensity (a) $D=0.1$, (b) $D=0.3$, (c) $D=0.4$, (d) $D=0.5$, (e) $D=0.7$, (f) $D=0.9$.

electrical activities in mode if possible instead of onefold mode in electrical activities from the previous neuronal models. To confirm the generality of this model, another group of parameters are used as $\alpha=0.4$, $\beta=0.02$, $k_1=0.4$, $k_2=0.5$, $k=0.9$, and results are plotted in Fig. 4 for external forcing current $I_{\text{ext}}=1.1$.

It is confirmed that quiescent state in neuron can excited and the electrical activities can present sudden spiking intermittently, the potential mechanism could be that the magnet flux in neuron (membrane) are changed in irregular way. Furthermore, the external electromagnetic radiation is imposed on neuron to observe the mode transition from spiking state to other states, and the results are plotted in Fig. 5. In Fig. 6, the mode transition from bursting state to other states is detected by imposing larger external forcing from electromagnetic radiation.

Indeed, the spiking state can be changed to different modes in electrical activities by applying appropriate intensity of electromagnetic field. For example, in Fig. 5(a), the spiking state is suppressed to present period 4, period 2 and then greatly suppressed in amplitude. In Fig. 5(b), the initial spiking state is changed into period 3, period, 2, period 1, period 4, period 1, period 6. In Fig. 5(c), it exists period 4, period 1, period 2, and period 6. In Fig. 5(d), it shows period 1, period 3, period 4, period 5, period 2, period 5. In Fig. 5(e), it finds period 3, period 6, period 2. In Fig. 5(f) period 2, period 6, period 4, period 2, period 6. That is to say, the initial spiking state can be adjusted to generate multiple modes in electric activities of neuron when neuron is exposed to appropriate external electromagnetic radiation. We also checked this case when initial state is set as bursting state, and the results are plotted in Fig. 6.

The results in Fig. 6 show that bursting state can be suppressed under appropriate intensity of electromagnetic field. The electric activities show that multiple modes (bursting and spiking) occurs alternatively. The mode transition in electric activities becomes detectable and observable by increasing the intensity of external electromagnetic field. Extensive numerical studies were carried out to find similar phenomenon by setting appropriate feedback k, k_1, k_2.

In a summary, the improved neuron model holds more bifurcation parameters and the effect of electromagnetic induction in cell could be considered. As a result, the effect of magnet flux is described by the fourth variable in the improved Hindmarsh–Rose neuron model. The electromagnetic field often is in random and can change the distribution of field, magnet flux of cells, thus the electromagnetic field is described by using Gaussian white noise. In fact, periodical type of electromagnetic field is also investigated in extensive numerical studies, and multiple types of modes in electric activities could be observed as well. In some previous works, multiple modes in electrical activities could be observed by adjusting more bifurcation parameters synchronously [38]. For our presented neuronal model, bifurcation and Fast Fourier Transform analysis could also be carried out for further investigation of the coexistence of multiple modes in electrical activities. The scheme of bifurcation analysis [39–44] in neuronal models can throw light on understanding the mode transition in neuronal activities. Further investigation could be carried out on our model in case of network,

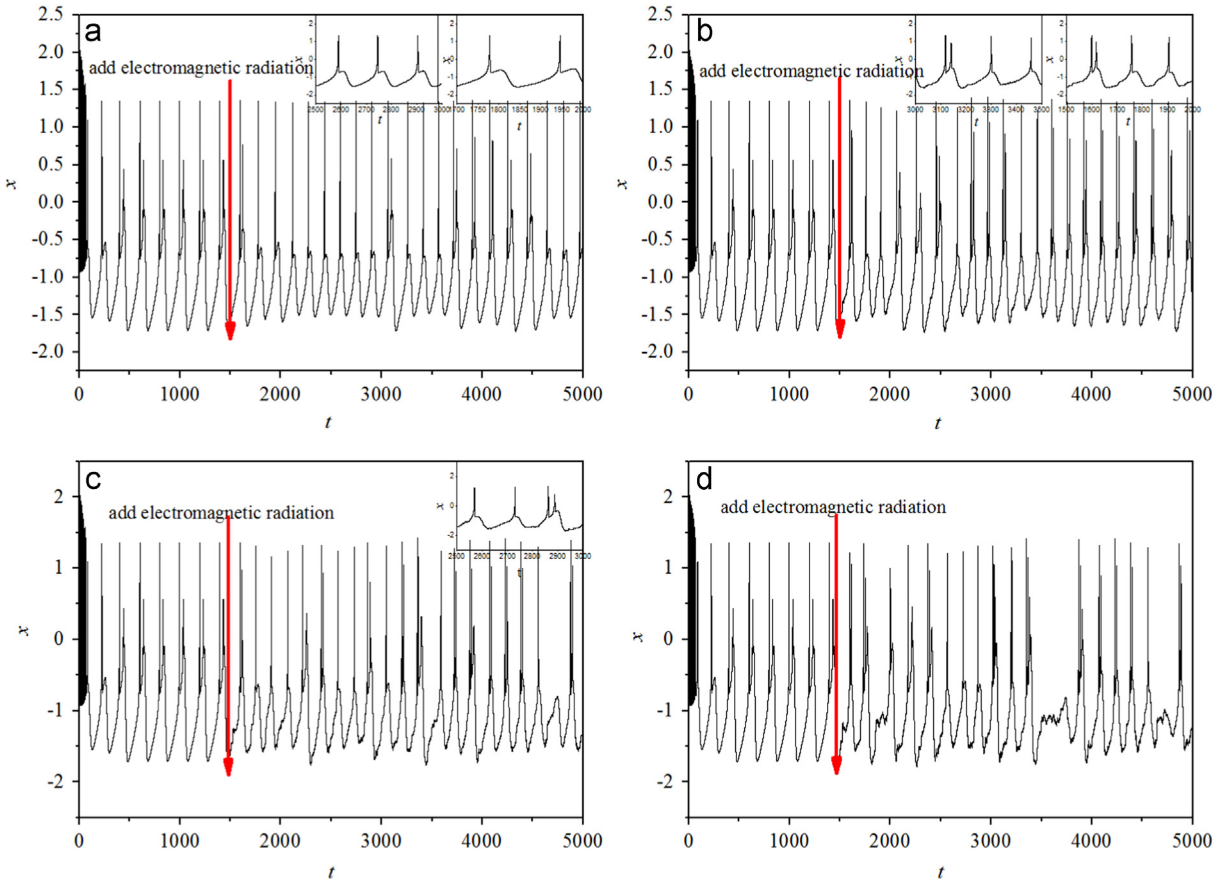

Fig. 6. The transition of electrical activities in an isolate neuron when electrical field radiation is switched on $t=1500$ time units, and external forcing current $I_{\mathrm{ext}}=1.71$. For intensity (a) $D=0.1$, (b) $D=0.4$, (c) $D=0.6$, (d) $D=0.9$.

synchronization problems; for example, the synchronization of neuron induced by internal electromagnetic radiation, desynchronization of coupled neurons induced by blocking in channels, thus the stability of collective electric behavior could be understood. Readers also can extend this scheme on biological neuron model such as Hodgkin–Huxley model so that the effect of ion channels could be considered. The authors of this paper wish readers in this field can extend this work and present biological neuron model under electromagnetic induction and radiation, and the parameter regions should be further confirmed by experiments.

3. Conclusions

A new neuron model is developed from the three-variable Hindmarsh–Rose neuron model by detecting the effect of electromagnetic induction. The dynamical behaviors become more complex and interesting by introducing more bifurcation parameters. Most of the previous neuronal model just produces sole mode in electrical activities under external forcing. Indeed, multiple modes in electrical activities of neurons can be reproduced by adjusting more than two bifurcation parameters if possible. We argue that the effect of electromagnetic induction [45] should be considered in cell and neuron during the fluctuation of membrane potentials and changes of ion concentration in cells. For this guidance, we suggest that magnet flux should be considered into the model and appropriate terms are set in the model according to consistence of physical units. According to the improved neuronal model, external forcing can generate a multiple of modes in electrical activities, it indicates that neurons can select appropriate electric activities in mode due to self-adaption.

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