Advances in Cognitive Neurodynamics

José M. Delgado-García
Xiaochuan Pan
Raudel Sánchez-Campusano
Rubin Wang *Editors*

Advances in Cognitive Neurodynamics (VI)

Proceedings of the Sixth International Conference on Cognitive Neurodynamics – 2017

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Advances in Cognitive Neurodynamics

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Preface

The 6th International Conference on Cognitive Neurodynamics (ICCN2017) was held in Carmona (Seville), Spain, from August 1–5, 2017. It is one of the series conferences held biennially since 2007, with support from the international journal "Cognitive Neurodynamics" (Springer). The research field of cognitive neurodynamics is the frontier of union where experimental and mathematical/computational neuroscience converge with cognitive neuroscience. Experiments generate a huge amount of neural data that must be treated correctly to obtain the best outcomes and the most accurate interpretation of them. At the same time, mathematical/computational methods and modeling are applied to understand and reveal dynamic principles on brain structure and functions concerning some cognitive processes such as brain oscillations, learning and memory, and neural plasticity among other higher-order brain functions or dysfunctions. Undoubtedly, cognitive neurodynamics is highly interdisciplinary, where researchers from biomedical sciences, neuroscience, cognitive neuroscience, mathematics, physics, computer science, technological science, and engineering contribute together to the advance in this field. The series conferences of ICCN provide very good opportunities for scientists from various fields to review their achievements, to share their ideas, and to promote the development of this field.

ICCN2017 attracted more than 100 participants from 17 countries (Australia, Belgium, China, France, Germany, Italy, Japan, New Zealand, Portugal, Russia, Spain, South Korea, Sweden, Switzerland, The Netherlands, United Kingdom, and United States of America), who made this conference a successful and memorable scientific event. There were 6 plenary lectures by leading scientists in the field of cognitive neurodynamics, 12 symposia (with 60 oral presentations) also by prominent researchers, and 1 poster session (a total of 38 posters) by both researchers and PhD students. Posters were permanently displayed along the whole meeting, allowing a long time for questions and discussions. The plenary speakers were Profs. Drs. Pierre-Paul Vidal (France), Salvador Martínez (Spain), Chris De Zeeuw (The Netherlands), Yoshikazu Isomura (Japan), Guo-Qiang Bi (China), and Wu Li (China). The organizers of the symposia were Drs. Alberto Ferrus (Symposium 1); Jan Lauwereyns (Symposium 2); Laura M. Roa

(Symposium 3); Agnès Gruart (Symposium 4); José L. Cantero (Symposium 5); Yutaka Yamaguti, Akihiro Yamaguchi, and Ichiro Tsuda (Symposium 6); Juan de los Reyes Aguilar (Symposium 7); Yoshikazu Isomura (Symposium 8); Hans Liljeström (Symposium 9); Toshishisa Tanaka and Jianting Cao (Symposium 10); Raudel Sánchez-Campusano and Steven L. Bressler (Symposium 11); and Xu Lei (Symposium 12). In several symposia, a tribute was paid to Walter J. Freeman (January 30, 1927–April 24, 2016) for his groundbreaking contributions to cognitive neurodynamics.

The topics of the conference covered almost all the branches of cognitive neurodynamics, from micro-, meso-, to macro-level dynamics, their applications, and some related topics, especially including neural coding, neural population dynamics, sensory and motor dynamics, EEG, fMRI and brain imaging, global cognitive functions, realistic neural networks, oscillation and synchronization, neural computing, brain computer interface, cognition disorder, multiscale neurodynamics, and also the coordination dynamics from neural-to-mental-to-social systems.

This volume fairly well reflects the large span of research presented at ICCN2017 conference. The papers in this volume (51 chapters by a total of 147 authors) were organized in the following five parts: (I) Neural Dynamics in Motor and Sensory Systems and in Cognitive Functions (10 chapters); (II) Cognitive Network and Multi-Scale Neural Network Dynamics (10 chapters); (III) Neuroengineering, Neuroinformation, and Brain Computer Interaction (10 chapters); (IV) Modelling Higher-Order Functions and Dysfunctions (10 chapters); and (V) Oscillation, Synchronization, Neural Plasticity, and Coordination Dynamics from Neural to Social Systems (11 chapters). All submitted papers were peer-reviewed by experts in the field based on originality, significance, quality, and clarity, under the coordination of the contact volume editor Dr. Raudel Sánchez-Campusano (Pablo de Olavide University). From the organizing committee, we thank all the authors for the outstanding quality of the contributions to ICCN2017 conference proceedings.

Finally, we wish to express our gratitude to all those who made ICCN2017 conference and this proceedings volume possible. In addition to all the contributing authors, we especially thank the plenary speakers, the symposium organizers, and the helpful students who assisted during the conference. We gratefully acknowledge sponsorship from CeslatiC Foundation, Carmona City Hall, Cibertec S.A., Univerlab S.L., BioAvan I+D+I, Olavide en Carmona Center, and Pablo de Olavide University, for the ICCN2017 conference. Also we thank the journal “Cognitive Neurodynamics” by Springer for the publication of this book series.

The 7th conference in the series – ICCN2019 – will be held in Alghero, Sardinia (Italy), September 29–October 2, 2019; organized by Prof. Alessandro E.P. Villa and colleagues (NeuroHeuristic Research Group and LABEX – HEC Lausanne, University of Lausanne, Switzerland). We have no doubt that ICCN2019 will be as successful as the previous ones.

Seville, Spain

José M. Delgado-García
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Neural Dynamics in Motor and Sensory Systems and in Cognitive Functions

Chapter 1
Decomposition of Superimposed Chaotic Spike Sequences by Using the Bifurcating Neuron

Akihiro Yamaguchi, Yutaka Yamaguti, and Masao Kubo

Abstract In this study, decomposition of superimposed chaotic spike sequence was investigated from the view point of neural information coding. We construct simple network of bifurcating neuron and introduce the coupling model to decompose superimposed chaotic spike sequences. The decomposing performance was demonstrated by the numerical simulation and evaluated by the ratio of synchronized spikes. As a result, for the superimposed two chaotic spike sequences, approximately 90% of spikes were correctly decomposed.

Keywords Chaotic synchronization · Bifurcating neuron · Neural coding

1.1 Introduction

The temporal structure of spike firing timing is considered to play an important role in information processing in the brain. In our previous studies, we have shown segmentation and feature linking of input images by using the chaotic cellular neural network to achieve chaotic synchronization of evoked spike sequences [1, 2]. The neuron model used to generate spike sequences with chaotic inter-spike intervals was based on the bifurcating neuron [3] and described by the spike response model [4]. The bifurcating neuron is a chaotic integrate-and-fire neuron that was introduced by Lee and Farhat [3].

Advantages of a chaotic spike sequence include its diversity and exponential decay of correlation function. By using these properties, we were able to distinguish different chaotic spike sequences and link identical chaotic spike sequences. In

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this study, decomposition of superimposed chaotic spike sequences was investigated from the viewpoint of neural information coding by employing a simple network model that we constructed using the bifurcating neuron. In the following sections, we describe our network model to decompose superimposed chaotic spike sequences and present the results of the numerical simulations.

1.2 Simple Network Model to Decompose Superimposed Chaotic Spike Sequences

In our model, the bifurcating neuron [3] is employed to generate and to decompose a chaotic spike sequence which inter-spike interval dynamics is chaotic. In this section, we explain the dynamics of the bifurcating neuron and our simple coupling model of bifurcating neuros to decompose superimposed chaotic spike sequences.

1.2.1 Bifurcating Neuron

In this study, we describe the bifurcating neuron as a form of spike response model (SRM) [4] to clarify the coupling term. Here, we denote the i-th neuron as $n^{(i)}$. Let $u^{(i)}(t)$ be an internal potential of $n^{(i)}$ at time t and its dynamics is defined as:

$$u^{(i)}(t) = u_{rest} + \eta^{(i)}(t) + \nu^{(i)}, \tag{1.1}$$

where u_{rest} is the resting potential, $\nu^{(i)} \in [-\nu_0, +\nu_1]$ is the uniform noise, and $\eta^{(i)}(t)$ is a kernel function of internal state dynamics. In the case of the bifurcating neuron, $\eta^{(i)}(t)$ is defined as:

$$\eta^{(i)}(t) = \eta_0 \left(t_{last}^{(i)}, \phi^{(i)}\right) + \alpha \, \left(t - t_{last}^{(i)}\right); \tag{1.2}$$

$$\eta_0 \left(t, \phi\right) = A_\eta \sin\left(2\pi\omega \, t + \phi\right), \tag{1.3}$$

where $t_{last}^{(i)}$ is the last firing time of $n^{(i)}$ and the constant α is the linearly increasing ratio of $\eta^{(i)}(t)$. The internal potential $u^{(i)}(t)$ is linearly increasing by the η kernel. When $u^{(i)}(t)$ exceeds the threshold value θ, $n^{(i)}$ is fired and $u^{(i)}(t)$ is reset to the initial potential given by the background oscillation $\eta_0(t, \phi)$. The constants A_η, ω, and ϕ are the amplitude, the frequency, and the phase of the background oscillation, respectively. The dynamics of the bifurcating neuron is shown in Fig. 1.1a.

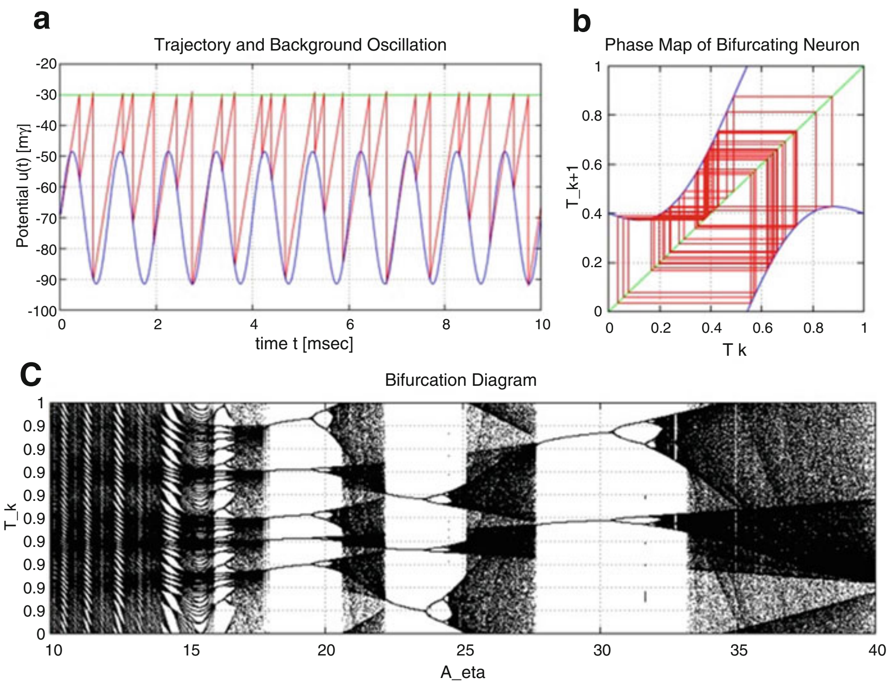

Fig. 1.1 The dynamics of the single bifurcating neuron. (**a**) Example of the time evolution where $\alpha = 100$, $\theta = -30$, $u_{rest} = -70$, $A_\eta = 21.5$, $\omega = 1$, and $\phi = 0$. The threshold value θ, the internal potential $u(t)$, and the background oscillation are represented by the green line, the red line, and the blue line, respectively. (**b**) The return map of the phase T_k of the firing time. (**c**) The bifurcation diagram of the single bifurcating neuron where the abscissa is the amplitude of background oscillation A_η and the ordinate is the phase T_k of the firing time

In the case without the noise term $\nu^{(i)}$, the $k+1$-th firing time $t_{k+1}^{(i)}$ of $n^{(i)}$ is simply determined by the map f and the previous firing time $t_k^{(i)}$ such as:

$$t_{k+1}^{(i)} = f\left(t_k^{(i)}; \phi^{(i)}\right) = t_k^{(i)} + \frac{\theta - u_{rest} - \eta_0\left(t_k^{(i)}, \phi^{(i)}\right)}{\alpha} \tag{1.4}$$

Furthermore, the phase $T_k^{(i)} = t_k^{(i)} \ mod \ 1$ in the background oscillation is also determined by the one dimensional map:

$$T_{k+1}^{(i)} = F\left(T_k^{(i)}; \phi^{(i)}\right) = f\left(T_k^{(i)}; \phi^{(i)}\right) \ mod \ 1. \tag{1.5}$$

An example of map F is shown in Fig. 1.1b. As increasing A_η, dynamics of the phase $T_k^{(i)}$ shows various behavior including bifurcating one and chaotic one as shown in Fig. 1.1c.

1.2.2 Simple Network Model with Phase Response Coupling

Our network model consists of two types of neurons: a transmitter neuron and a receiver neuron. The transmitter neurons generate spike sequences with chaotic inter-spike intervals. The generated spike sequences are superimposed and inputted to the receiver neuron. The receiver neuron also generates spike sequences via its own dynamics and inputted sequences. These transmitter neurons with different inter-spike-interval dynamics are implemented by the bifurcating neuron (see Eq. (1.1)). In order to construct the network model, we introduce the coupling term to the bifurcating neuron. Let the set $\Gamma^{(i)}$ be a set of firing time of super imposed spike sequences inputted to the receiver neuron $n^{(i)}$ from transmitter neurons such that:

$$\Gamma^{(i)} = \left\{ s_0^{(i)}, s_1^{(i)}, s_2^{(i)}, \cdots \right\}, \tag{1.6}$$

where $s_j^{(i)}$ $(j = 0, 1, \cdots)$ is the firing time of the neurons coupled to $n^{(i)}$. The dynamics of the bifurcating neuron with phase response coupling is defined as:

$$u^{(i)}(t) = u_{rest} + \eta^{(i)}(t) + \xi_-^{(i)}(t) + \xi_+^{(i)}(t) + \nu^{(i)}, \tag{1.7}$$

where $\xi_-^{(i)}(t)$ and $\xi_+^{(i)}(t)$ are the negative coupling term and the positive one, respectively.

These coupling terms are designed to synchronize to the input spikes if its own dynamics is the same with the dynamics of input spike sequences. The definition of the negative and positive coupling terms are as follows:

$$\xi_-^{(i)}(t) = \sum_{s \in \Gamma^{(i)},\ t_{last}^{(i)} \le s < t} \varepsilon_-\left(s, t_{last}^{(i)}\right); \tag{1.8}$$

$$\varepsilon_-^{(i)}\left(s, t_{last}^{(i)}\right) = \begin{cases} 0 & s \le t_{last}^{(i)} \\ -\beta_- \frac{s - t_{last}^{(i)}}{\Delta_\varepsilon} & t_{last}^{(i)} < s \le t_{last}^{(i)} + \Delta_\varepsilon \\ 0 & t_{last}^{(i)} + \Delta_\varepsilon < s \end{cases}, \tag{1.9}$$

and

$$\xi_{+}^{(i)}(t) = \sum_{s \in \Gamma^{(i)},\ t_{last}^{(i)} \leq s < t} \varepsilon_{+}\left(s, \widehat{t}_{next}^{(i)}\right); \tag{1.10}$$

$$\varepsilon_{+}^{(i)}\left(s, \widehat{t}_{next}^{(i)}\right) = \begin{cases} 0 & s < \widehat{t}_{next}^{(i)} - \Delta_{\varepsilon} \\ +\beta_{+} & \widehat{t}_{next}^{(i)} - \Delta_{\varepsilon} \leq s < \widehat{t}_{next}^{(i)} \\ 0 & \widehat{t}_{next}^{(i)} \leq s \end{cases}, \tag{1.11}$$

where β_{-} and β_{+} are nonnegative coupling constant, Δ_{ε} is coupling time range where input spike is affective, $\varepsilon_{-}^{(i)}$ and $\varepsilon_{+}^{(i)}$ are phase response curves, and $\widehat{t}_{next}^{(i)}$ is a predicted next firing time such that:

$$\widehat{t}_{next}^{(i)} = t + \frac{\theta - u(t)}{\alpha}. \tag{1.12}$$

If the time s of the arrived spike is within the range Δ_{ε} from the last spike firing time $t_{last}^{(i)}$, then the phase response is negative to delay the next firing time. Otherwise, if the time s is within the range Δ_{ε} from the predicted next firing time $\widehat{t}_{next}^{(i)}$, then the phase response is positive to hasten the next firing time.

1.3 Numerical Experiments

In order to examine the decomposing performance of the proposed network, we numerically simulate the four neurons network where $n^{(0)}$ and $n^{(1)}$ are transmitter neurons Eq. (1.1) and $n^{(2)}$ and $n^{(3)}$ are receiver neurons (see Eq. (1.7)).

The generated spike sequences of $n^{(0)}$ and $n^{(1)}$ are superimposed and input to the receiver $n^{(2)}$ and $n^{(3)}$. The parameter values of these four neurons are identical without the phase shift value $\phi^{(i)}$. For the decomposition, the phase shift values are chosen as $\phi^{(0)} = \phi^{(2)}$ and $\phi^{(1)} = \phi^{(3)}$. Since the phase shift value characterizes the shape of the return map of firing phase (Fig. 1.1b), the internal dynamics of $n^{(2)}$ and $n^{(3)}$ are the same with $n^{(0)}$ and $n^{(1)}$, respectively.

Numerical simulations were performed for three cases such as (1) $\beta_{-} > 0$ and $\beta_{+} = 0$, (2) $\beta_{-} = 0$ and $\beta_{+} > 0$, and (3) $\beta_{-} > \beta_{+} > 0$. Results of the numerical simulation for the case (3) are shown in Fig. 1.2. As shown in Fig. 1.2d–e, the receiver $n^{(2)}$ and $n^{(3)}$ synchronizes to the transmitter $n^{(0)}$ and $n^{(1)}$, respectively. The degree of synchronization is evaluated by the ratio of synchronized spikes between two neurons (Table 1.1). Here, the ratio of synchronized spikes is estimated by 10 trials of simulation and approximately 10,000 spikes are generated for each trial. For the case (3), approximately 90% of spikes are correctly decomposed by the synchronized response of receiver neurons.

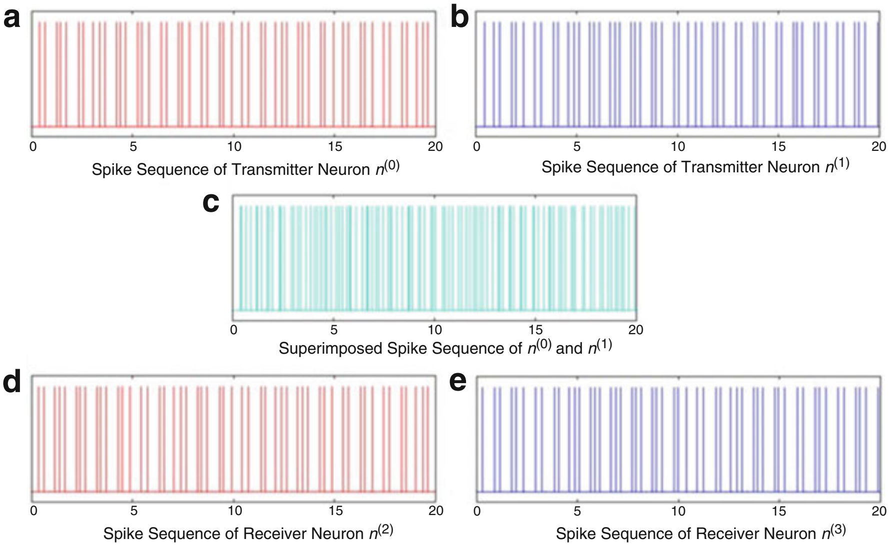

Fig. 1.2 Example of the numerical simulation of the proposed network model to decompose superimposed spike sequences, where $\beta_- = \beta_+ = 2.1$, $\Delta_\varepsilon = 0.05$, $\phi^{(0)} = \phi^{(2)} = 0$, $\phi^{(1)} = \phi^{(3)} = \pi$, and other parameters are same with Fig. 1.1a. (**a**) The spike sequence of the transmitter $n^{(0)}$. (**b**) The spike sequence of the transmitter $n^{(1)}$. (**c**) The superimposed spike sequence of $n^{(0)}$ and $n^{(1)}$. (**d**) The spike sequence of the receiver $n^{(2)}$. (**e**) The spike sequence of the receiver $n^{(3)}$

Table 1.1 Ratio of synchronized spikes between two neurons

	Ratio of synchronized spikes		
	$\beta_- = 2.1$	$\beta_- = 0$	$\beta_- = 2.1$
Target neurons	$\beta_+ = 0$	$\beta_+ = 2.1$	$\beta_+ = 2.1$
$n^{(0)}$ and $n^{(2)}$	$50.2 \pm 1.4\%$	$62.3 \pm 2.2\%$	$88.9 \pm 1.3\%$
$n^{(0)}$ and $n^{(3)}$	$19.8 \pm 0.7\%$	$20.9 \pm 0.5\%$	$20.1 \pm 0.6\%$
$n^{(1)}$ and $n^{(2)}$	$19.4 \pm 0.9\%$	$21.0 \pm 0.7\%$	$20.0 \pm 0.5\%$
$n^{(1)}$ and $n^{(3)}$	$49.2 \pm 1.6\%$	$63.6 \pm 2.1\%$	$89.4 \pm 2.1\%$
$n^{(0)}$ and $n^{(1)}$	$19.9 \pm 0.7\%$	$19.9 \pm 0.6\%$	$19.9 \pm 0.4\%$
$n^{(2)}$ and $n^{(3)}$	$19.3 \pm 0.5\%$	$23.5 \pm 0.5\%$	$22.5 \pm 0.6\%$

1.4 Summary and Discussion

In this study, we proposed the coupling model to decompose superimposed chaotic spike sequences generated by the bifurcating neuron. As a result, we demonstrated that two chaotic spike sequences with the different phase shift values are able to decompose by the proposed coupling model of the bifurcating neuron.

This result indicates two possibilities. One is that multiple information are simultaneously representable by the superimposed chaotic spike sequences. The other is that neural activity of different neurons is linkable by their selective synchronization if they obey the same chaotic dynamics. Although the proposed coupling model might be too artificial in order to apply the neural information coding in the real brain, we could demonstrate the possibility of chaotic spike sequence as a carrier of information. Further analyses of decomposing mechanism and performance are our future work.

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Chapter 2
Neural Energy Properties and Mental Exploration Based on Neural Energy Field Gradient

Yihong Wang, Xuying Xu, and Rubin Wang

Abstract Neural coding problem is one of the most important basic problems of cognitive neuroscience. The classic coding theories based on firing rate now encounter their own bottlenecks. Energy coding method studies the coding problem by the energy characteristics of neural systems which possesses the advantages of globality and economy. This research analyzed the energy coding theory in computational level and applied it to mental exploration and path optimization. First, we defined and calculated the neural energy supply and consumption based on the Hodgkin-Huxley model during two activity states using ion-counting and power integral method. Then the energy properties of each ion channel are analyzed. The energy efficiency of a neuron is 76% and above 100% under these two circumstances. Finally, we study the mental exploration by energy method and constructed an effective model to find and optimize the path to the target.

Keywords Energy coding · Mental exploration · Neural energy field · Place cells

2.1 Introduction

It is one of the most important questions in cognitive neural science that how the neural systems code and decode neural information [1]. Scientists have established phase coding, frequency coding, and group coding to encounter this problem. Unfortunately, the scope of these techniques is limited, and the definitions are vague [2]. Currently, no complete theory for neural coding and decoding has been accomplished to direct the research of global brain activities. One reason is that

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these coding theories are focusing on local neural activities and do not include the cross influence of large-scale neural activities. Furthermore, due to the nonlinear property of the neurodynamics, it is very hard to perfectly analyze the neural coding and decoding problem by classical coding methods. Neural activities and neural information processes should follow the principles of energy minimization and information transmission efficiency maximization [3], and neural system should be restricted by energy minimization regardless of suprathreshold or subthreshold activity. This is the economical essence of neural system because of evolution. Information transmission efficiency must maximize the energy utilization in a neural system; this property reflects the high efficiency of neural system for information processing. However, it is difficult to define and describe neural metabolic energy, neural electric energy, and the relationship between them. Some researches helped to understand the neural energy consumption and transformation [4], but they are not related to information coding by neuron group activity.

Some researchers have proposed a new method to study neural coding by energy [3]. In order to describe the relationship between bioenergy of the brain and the neural information processes of the prefrontal cortex, a biophysical model concerning neural circuit has been constructed. Furthermore, quantitative relationship between firing patterns and neural energy evolutionary process has been discovered. Based on these unique relationship, researchers developed the concept of energy coding and further calculated the energy of a single neuron [3]. Some interesting findings have been discovered during the study of the energy distribution properties of structural neural networks. These ideas have laid the foundation for energy coding research of the functional neural network.

Although many scientists achieved remarkable works studying neural energy, a basic question has been ignored, which is how to define and distinguish neural energy supply and consumption. The neural energy concept is quite vague in many research; as a result, we need to clarify the different type of neural energy. In this research, we will analyze this problem by energy coding method.

Energy coding method can be used to study variety of cognitive activity, such as spatial representation and learning. The concept of the cognitive map can be used to solve the navigation problems in environment such as self-locating, target-searching, and pathfinding. Place cells in hippocampus are the biological foundation of cognitive map, which are firstly found by the Nobel Prize winner O'Keefe in the hippocampus with an electrophysiological method [5]. Redish and Touretzky found that the hippocampus possesses ability of spatial memory and spatial navigation in rodent animal [6]. However, the deficiency of cognitive map model is that it took tremendous of physical explorations to form path vector. The agent needs to explore the actual spatial environment continually through the physical movements, which waste much time and energy. Our study can make up the defects, and physical exploration can be improved to mental exploration. Mental exploration was firstly introduced by Hopfield [7]. He adapted plane attractor and substituted the mental exploration in the virtual space for the heavy process of physical exploration. Mental exploration has some obvious advantages compared to physical exploration [7]. However, it was first based on the artificial neural network, without direct physiological significance. Furthermore, during the process of pathfinding, there is no demand for learning speed and path efficiency. In our work, based on Hopfield's theory, neural energy coding method with clearer biological meanings is adopted, and the firing power of place cell is the key to guide mental exploration. An efficient mental exploration path can be achieved by this method, which also possesses the function of path optimization. It is an effective application of neural energy coding method.

2.2 Neural Energy Properties

In order to study the neural energy and its reflection of neural information, we first should solve basic question that has been ignored for a long time, which is how to define and distinguish neural energy supply and consumption. Let us consider the energy transformation in the neuron. First, ATP hydrolyzes to provide chemical energy to ion pump, especially the Na^+/K^+ pump. Then the ion pump works to transport ions against the concentration gradient to preserve electrical potential. It ejects Na^+ and injects K^+ across the cell membrane. This process is equivalent to charging a battery, during which chemical energy is transformed to electric potential energy. When the stimulus occurs, ions flow through ion channels pushed by the electric field force, the potential energy preserved in the membrane capacitor is released and turned into joule heat due to the resistance effect of ion channels. During this process, an action potential fired or subthreshold activity occurs. Finally, ion pump must transport the ions again to recover the membrane potential, and the chemical energy of the ATP will be consumed again. This is an energy cycle of a neuron. To conclude, the chemical energy of ATP is the energy supply for the neuron, and the electric energy carried by ion currents to transmit neural signal is the energy consumption by the neuron. Apparently, energy should be conserved during lager scale of time, but in small time interval energy supply and consumption are not really matched in every moment. This property makes it possible to study brain activity status based on energy supply and consumption properties.

From the former discussion, it can be deducted that energy supplied to a neuron is the energy released by ATP which consumed by the ion pump. The energy consumed by a neuron is the joule heat transformed from electric potential energy. It is also known that every 3 Na^+ ions pumped out of a cell membrane, one ATP molecule is consumed [8]; each mole of ATP molecules can release between 46 and 62 kJ free energy. After Na^+ flow into neuron during neural activity, the Na^+/K^+ pump will expel the same amount of Na^+ to reset the resting membrane potential. Thus, if the amount of Na^+ flow into neuron can be counted, the ATP consumption could be calculated [9]. And based on a proper neuron ion channel model, joule heat can be obtained [4]. Fortunately, all these characters can be deduced by the classical Hodgkin-Huxley model (H-H model) as shown below (Fig. 2.1).

The differential equation is

$$C_m \frac{dV_m}{dt} = g_l\left(E_l - V_m\right) + g_{Na} m^3 h\left(E_{Na} - V_m\right) + g_K n^4\left(E_K - V_m\right) + I \quad (2.1)$$

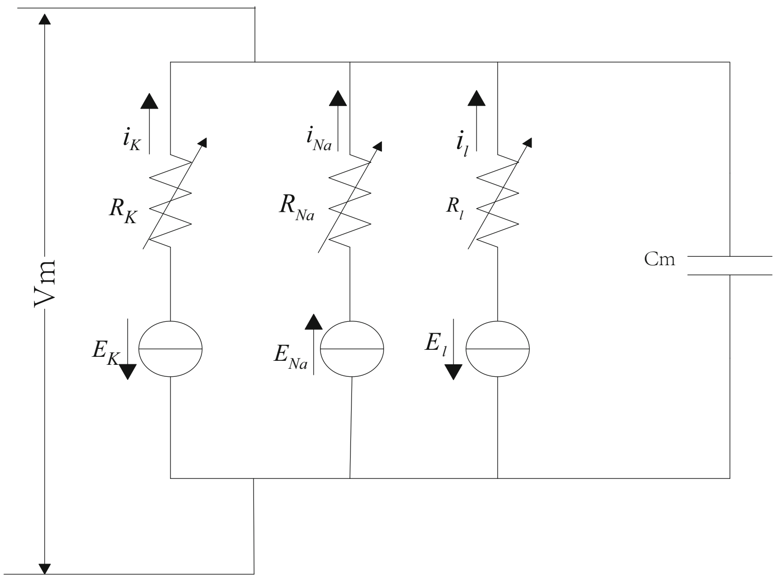

Fig. 2.1 Circuit of Hodgkin-Huxley model (H-H model)

where C_m is membrane capacitance of a neuron, V_m is membrane potential, E_{Na} and E_K are Nernst potentials of Na^+ and K^+, and El is the potential, while leakage current is zero. g_l, g_{Na}, and g_K are, respectively, leakage conductance, Na^+ channel conductance, and K^+ channel conductance.

Energy supplied by ATP can be calculated based on the H-H model:

$$E_s = \frac{\lambda}{3\ eN_A} \int_t g_{Na} m^3 h \left(E_{Na} - V_m\right) dt \tag{2.2}$$

where λ is amount of energy released by one mole ATP; e is the elementary charge, which is 1.6×10^{-19} coulomb; and NA is Avogadro constant, and the integrand is the current of the Na^+ channel [4]. By integrating the H-H equation at a particular time interval, we are able to calculate the energy consumed by a neuron during this time period [4]:

$$E_c = \int_t \left[V_m I + i_{Na}\left(E_{Na} - V_m\right) + i_K\left(E_K - V_m\right) + i_l\left(E_l - V_m\right)\right] dt \tag{2.3}$$

As soon as energy supply and consumption are calculated, energy efficiency can be defined by percentage of energy consumption over supply:

$$\eta = \frac{E_c}{E_s} \times 100\% \tag{2.4}$$

We can also calculate the synchronicity of energy consumption and currents of different ion channels. As shown in Fig. 2.2, Na^+ (red) and K^+ channels consumed most of the total electrical power (green), and the energy consumption of leakage (yellow) and stimulus currents (fuchsia) are relatively small. Figure 2.2a is the energy during action potential, and Fig. 2.2b is subthreshold activity.

Integrating the power shown in Fig. 2.2, we can get the energy consumed by a neuron during these periods. Meanwhile, energy supplied to a neuron can also be calculated by integrating Na^+ current and counting the ions. Results are shown in Table 2.1.

In conclusion, the energy properties of a neuron are significant under two states; these differences may provide an insight to further understanding neural information coding and processing problem.

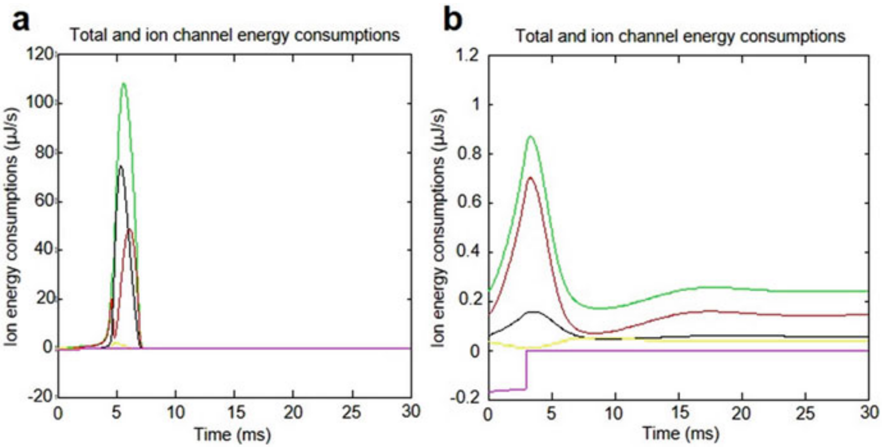

Fig. 2.2 Energy consumption of ion currents [10]

Table 2.1 Energy properties of a neuron [10]

	Super-threshold activity	Subthreshold activity
Energy supplied	2.468×10^{-7} J/cm^2	8.75×10^{-9} J/cm^2
Energy consumed	1.879×10^{-7} J/cm^2	8.31×10^{-9} J/cm^2
Synchronicity	0.782	0.96
Phase difference	38.5°	16.26°
Energy efficiency	76%	105.3%