神经网络
Neural Networks
第十三章

神经元集群

史忠植

中国科学院计算技术研究所
http://www.intsci.ac.cn/

内容提要

- 13.1 概述
- 13.2 大脑皮层
- 13.3 嗅觉神经系统的K系列模型
- 13.4 皮层功能柱的细胞结构
- 13.5 皮层功能柱理论模型
- 13.6 集群编码
- 13.7 神经元集群时空编码

Neural Representation of moving direction

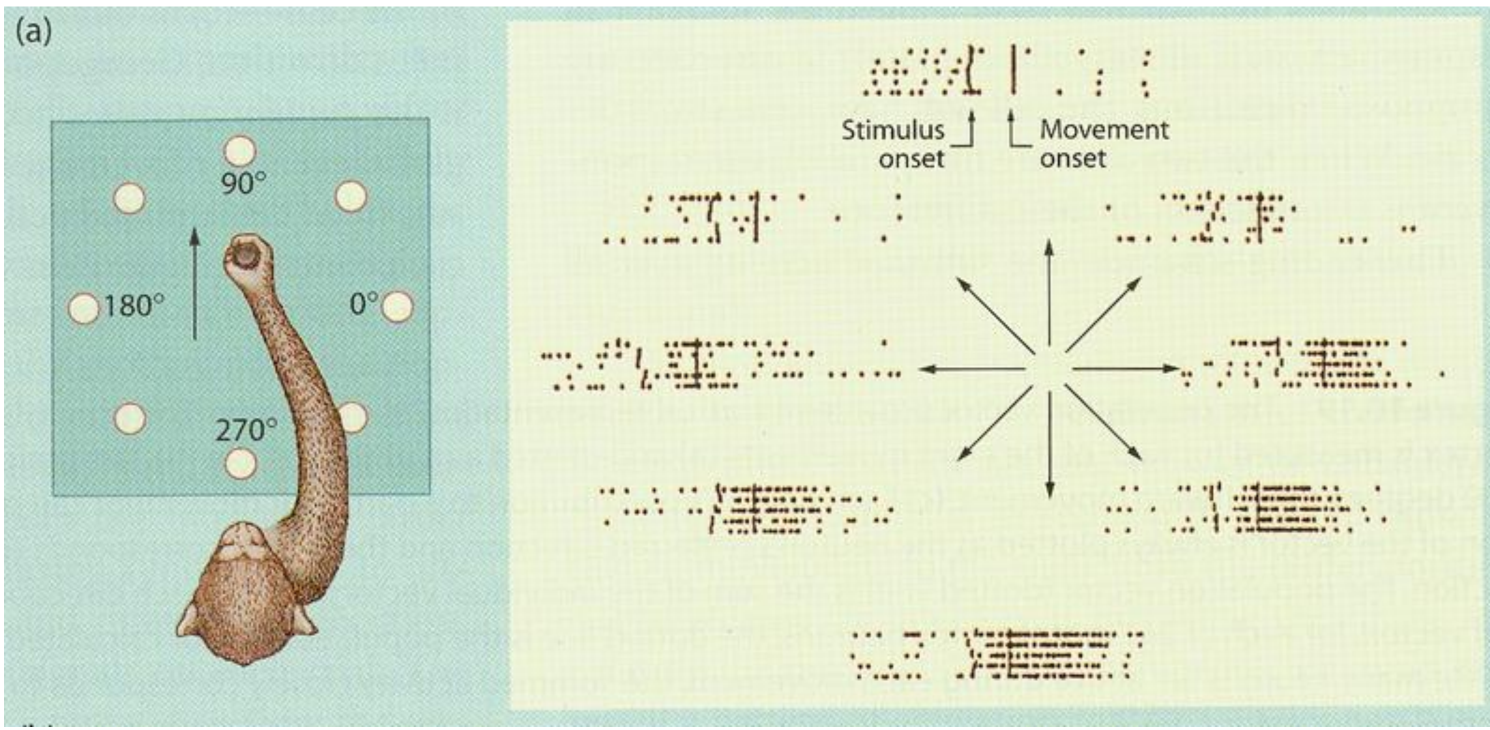
•Two pieces of information are important for representing the dynamical aspects of external objects, namely, the moving speed and the moving direction of objects.

•A. Georgopoulos's group carried out a series elegant experiments to explore the neural representation of moving direction.

•It is one of the few examples in which the coding scheme is relatively well understood.

Experiment observations

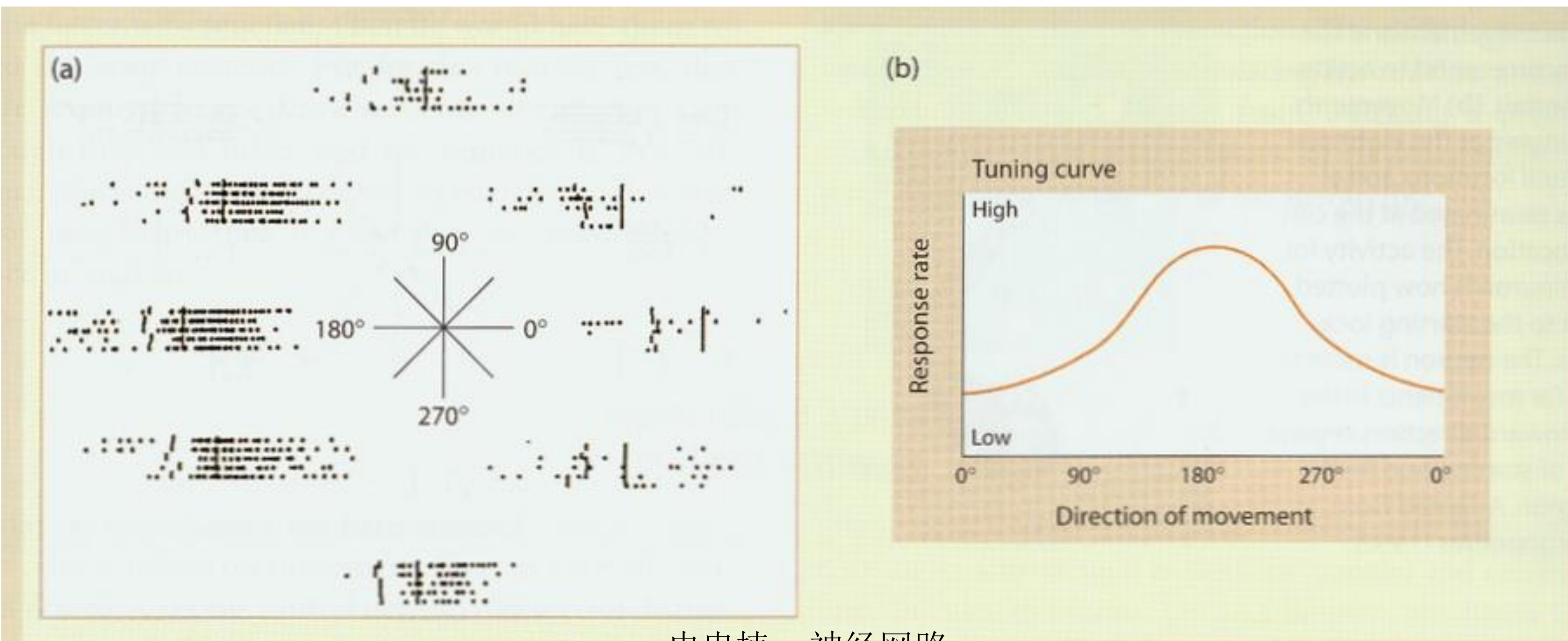
- In the experiment, the monkey is guided to move the lever in the center of apparatus to one of eight peripheral locations.
- Neural activities in the motor area are recorded.



All pictures from M. Gazzaniga et al. *Cognitive Neuroscience*, unless otherwise stated.

Preferred stimulus and tuning curve

- *Preferred stimulus*: for each neuron, there is a stimulus value by which the neuron has the maximum response.
- *Tuning curve*: the function mapping between the neural activity (measured by mean firing rate) and the stimulus value.
  - Noises always exist



Why population code?

- How is the moving direction encoded by neural activities?
- By the most active neuron? This sounds reasonably if there is no noise, but it does not work in practice because of large fluctuations in neural activities.
- By a population of neurons?
  All active neurons contain a piece of information about the stimulus, why don’t we consider all of them jointly encode the moving direction. It has at least one apparent advantage of averaging out noises in individual neurons, since they are (*partially*) independent.
- Georgopoulos et al. proposed an idea to reconstruct the moving direction from the observed neural activities.

Mathematical Modeling of Neuronal Response

- The smooth bell-shape tuning curve is often modeled by the Gaussian (or cosin) function:

$$f_i(x) = \exp[-(x-c_i)^2 / 2a^2]$$

$f_i(x)$: the mean firing rate of the ith neuron

x: the stimulus

c_i: the neuronal preferred stimulus

a: the tuning width

- For neural activity in one trial

$$r_i = f_i(x) + \varepsilon_i$$

ε_i: a random number of zero mean, representing noise

Population Vector

•Georgopoulos's idea: the neural system reads out the moving direction by the average of preferred stimuli of all active neurons weighted by their activities.
This sounds reasonable since more active neurons, whose preferred stimuli are more likely close to the true stimulus, and hence should contribute more on the final vote.

$$\vec{v} = \sum_i \frac{r_i}{Z} \vec{c}_i$$

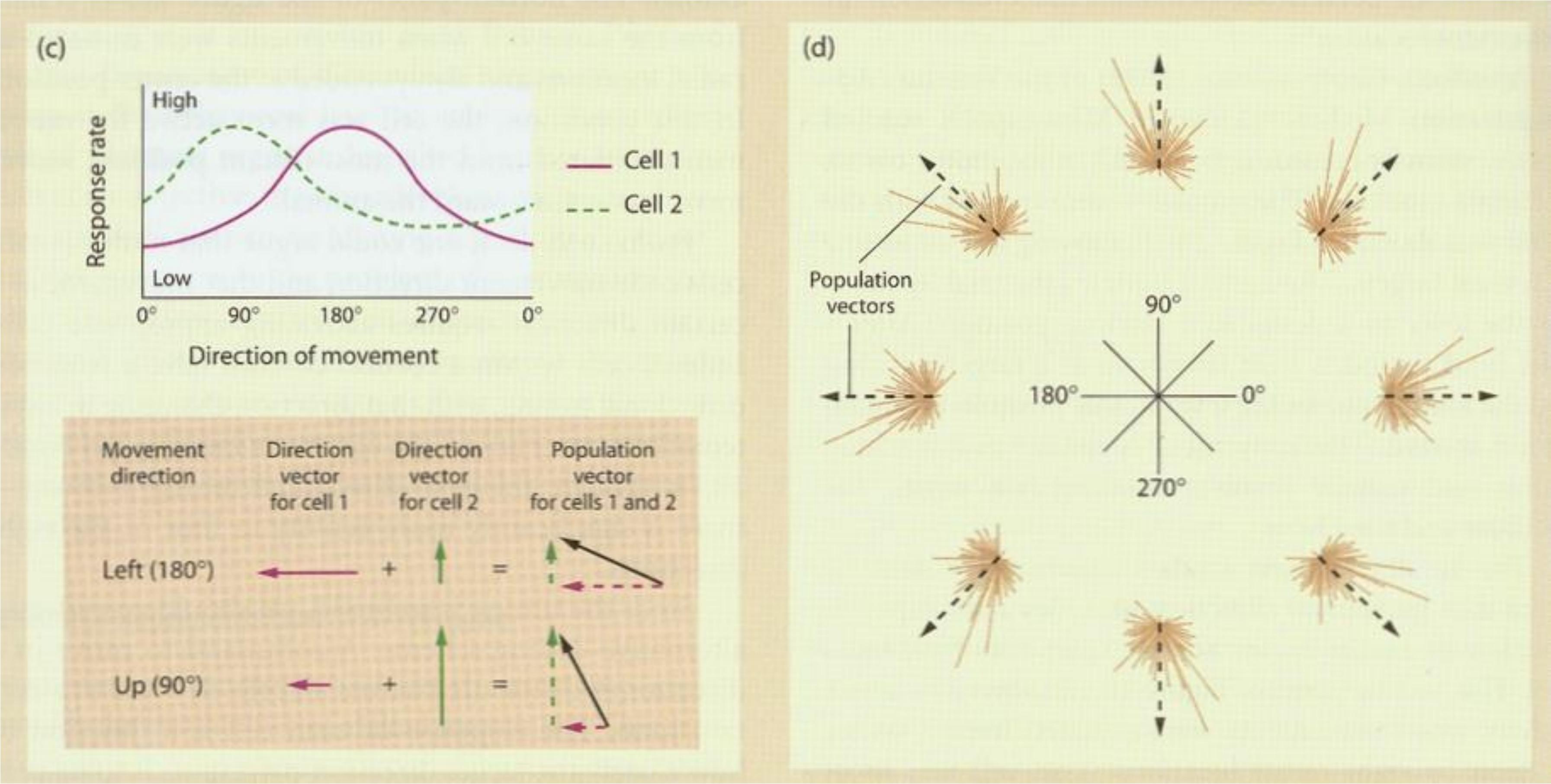
$\vec{v}$: the decoded moving direction

$\vec{c}_i$: the preferred direction of the *ith* neuron

$r_i \vec{c}_i$: the contribution from the *ith* neuron

$Z = \sum_i r_i$ the normalization factor

An illustration of Population Vector



The paradigm of population coding

•Population vector demonstrated that information can be accurately represented by the joint activities of a population of neurons in a noise environment. This coding strategy of using a population of neurons to represent stimulus is called *population coding*.

•The idea of population coding is also found in the representation of moving direction in other parts of cortex, and the representation of other stimuli, such as the orientation of object and the spatial location.

•Population coding seems to be a general framework for information processing in neural systems, and worth to be analyzed in more detail theoretically.

The mathematical model of population coding

- The encoding phase

$$x \rightarrow \mathbf{r} = \{r_i\}, \quad \text{for } i = 1, \ldots, N, \quad N \text{ is the number of neurons}$$

$$r_i = f_i(x) + \varepsilon_i$$

The encoding process is specified by the conditional probability $p(\mathbf{r} \mid x)$, i.e., the probability that the neural activities $\mathbf{r}$ is generated given the stimulus x is presented.

- The decoding phase

$$\mathbf{r} \xrightarrow{\text{infer}} x$$

Population vector is one of many inference strategies.

功能柱

20世纪60年代末，美国科学家发现，在大脑视觉皮层中，具有相同图像特征选择性和相同感受野位置的众多神经细胞，以垂直于大脑表面的方式排列成柱状结构———功能柱。30多年来，脑研究领域一直将垂直的柱状结构看作大脑功能组织的一个基本原则。但是，传统的功能柱研究还不能阐释视觉系统究竟是如何处理大范围复杂图像信息的。

功能柱

- 1972年：Wilson-Cowan方程来描述功能柱；
- 1990年：Shuster等人模拟视皮层中发现的同步振荡；
- 1993年：Jansen等人提出了耦合功能柱模型产生了类EEG波形和诱发电位；
- 1994年：Fukai设计了功能柱式的网络模型来模拟视觉图样的获取；
- 1997年：Hansel等人根据视皮层朝向柱的结构构建了一个超柱模型，研究其中的同步性和混沌特性，并对朝向选择性的功能柱机理做出解释；
- 1998年：Fransén等人把传统网络中的单细胞代换成多细胞构成的功能柱，来模拟工作记忆

功能柱

中国科学院生物物理所 视觉信息加工重点实验室
中国科学院计算研究所
李速[1] 齐翔林[1] 胡宏[2] 汪云九[1]

功能柱结构神经网络模型中的同步振荡现象

功能柱是一个振荡子，而且表明功能柱可以成为皮层多样化的节律活动的发生源，EEG中的各种节律均可以在结构具有普遍性的功能柱中找到生理基础。

功能柱

Rose-Hindmarsh方程来描述单神经元:

$$\dot{x} = y + ax^3 - bx^2 - z + I_{syn} + I_{stim}$$

$$\dot{y} = c - dx^2 - y$$

$$\dot{z} = r\left[s\left(x - x_0\right) - z\right]$$

x: 代表膜电位，

y: 表示快速回复电流，

z: 描述慢变化的调整电流，

I_{syn} 表示突触电流，

I_{stim} 表示外界输入

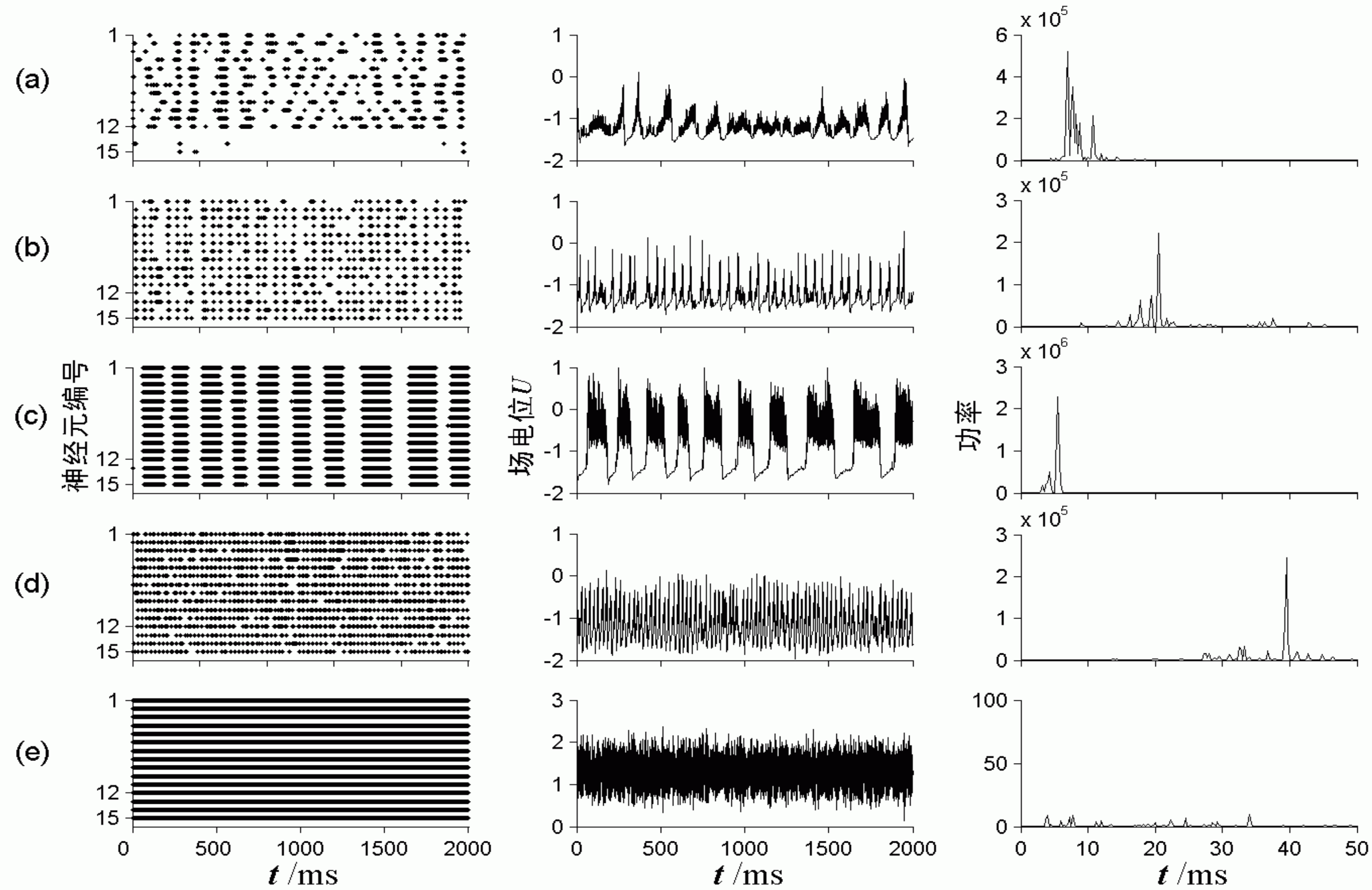
功能柱

模型采用基于电流的突触模型，在突触前细胞的每个动作电位都将触发突触后细胞的I_{syn}输入。突触电流I_{syn}表示为:

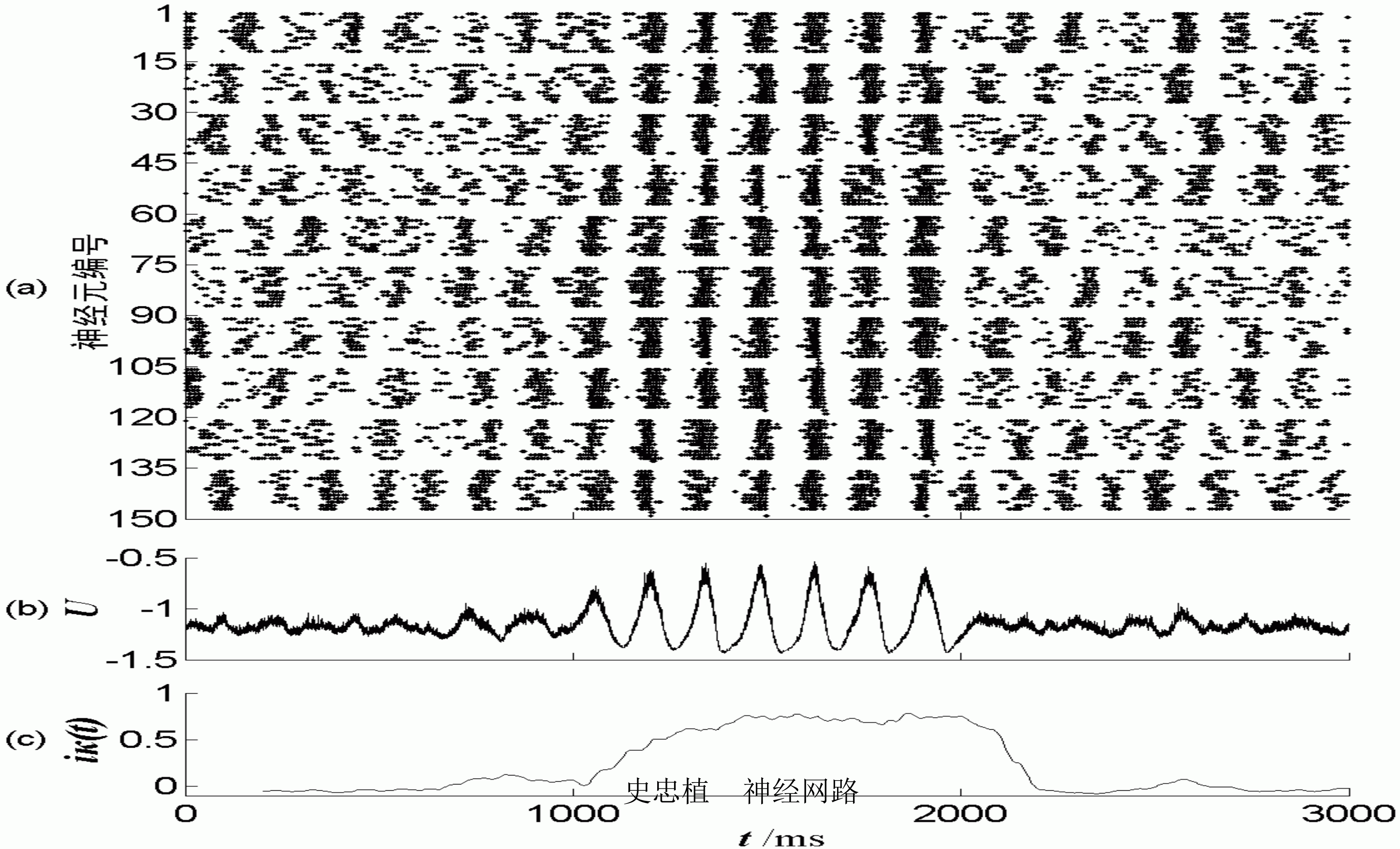
$$I_{syn} = g_{syn}V_{syn}(e^{-t/\tau_1} - e^{-t/\tau_2})$$

g_{syn} 为膜电导
τ_1, τ_2 时间常数
V_{syn} 表示突触后电位

功能柱

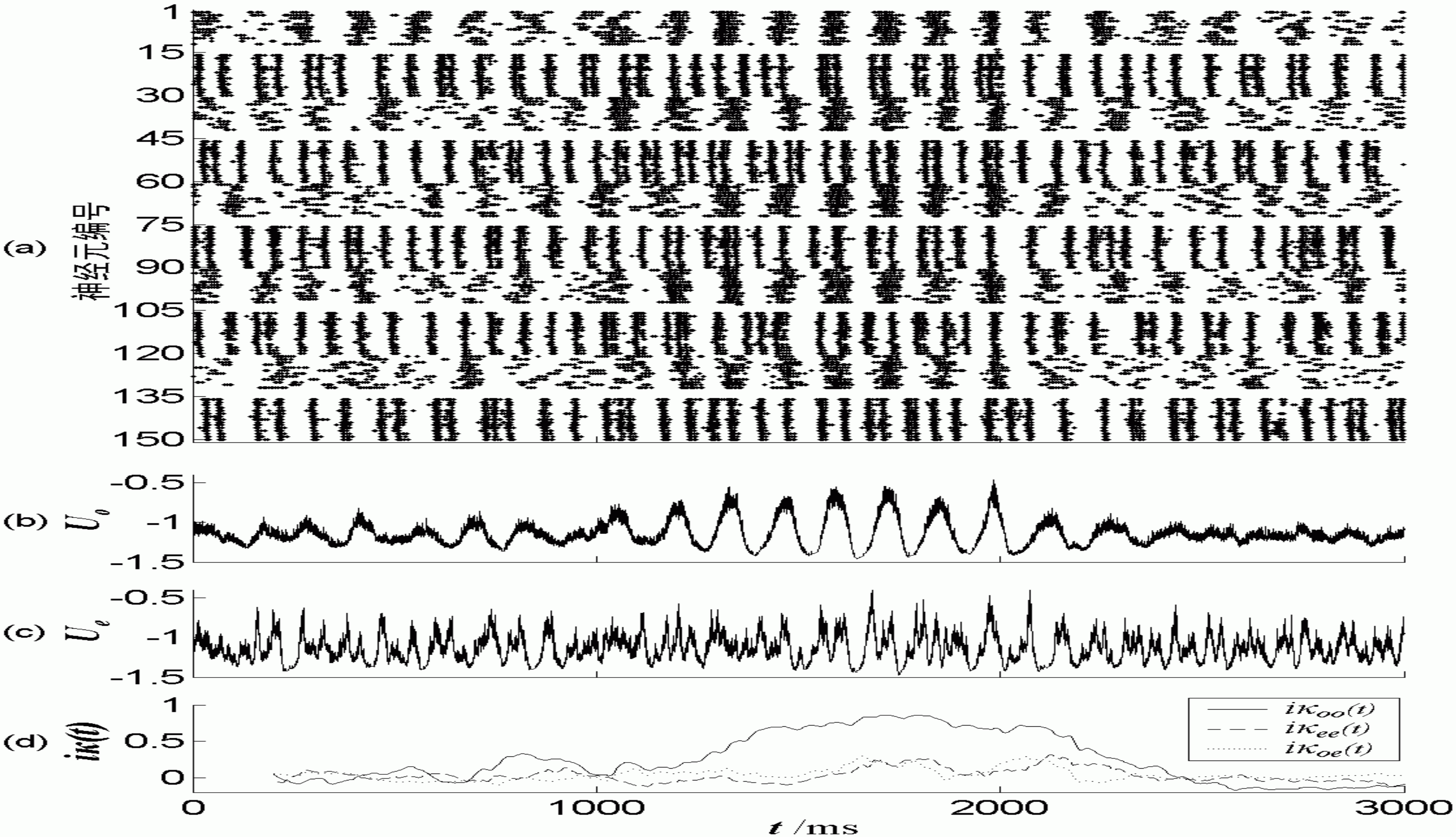


同源功能柱



1
15
30
45
60
75
90
105
120
135
150
(a)
神经元编号
(b)
U
-0.5
-1
-1.5
(c)
ik(t)
1
0.5
0
0
1000
2000
3000
t /ms

异源功能柱



(a)
神经元编号
1
15
30
45
60
75
90
105
120
135
150
(b)
U_o
-0.5
-1
-1.5
(c)
U_e
-0.5
-1
-1.5
(d)
$ik(t)$
1
0.5
0
$i\kappa_{oo}(t)$
$i\kappa_{ee}(t)$
$i\kappa_{oe}(t)$
0
1000
2000
3000
t /ms

功能柱

功能柱是一个振荡子，而且表明功能柱可以成为皮层多样化的节律活动的发生源，EEG中的各种节律均可以在结构具有普遍性的功能柱中找到生理基础。

功能柱

功能柱是介于单神经元和皮层脑区之间的一种中间层次的单元，理解这种中间层次的单元的活动特点，能够为脑科学中微观现象和宏观现象的研究之间建立一座桥梁

Thank You

Question!

Intelligence Science

http://www.intsci.ac.cn/