

# Model Neurons I: Neuroelectronics

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## 1 Electrical Properties of Neurons

- The structure of A Cell
- Physical Properties of Membrane: Capacitor and Resistance

## 2 Neuron Models

- Single-Compartment Model
- Integrate-and-Fire Model
  - Interspike-interval firing rate
  - Spike-Rate Adaptation
  - Voltage-Dependent Conductances

# Electrical Properties of Neurons

## The structure of A Cell

A cell is composed of nucleus, cytoplasm and **membrane**, etc.

There are microscopic particles (e.g. **ions** and molecules) inside and outside the cell.

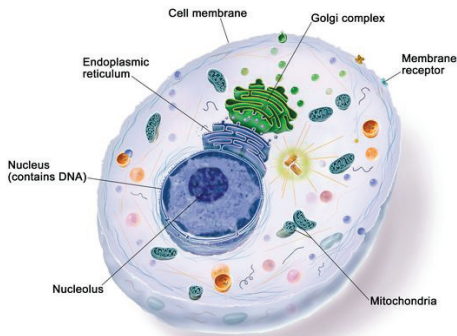


Figure 1: The structure of the animal cell.

# Electrical Properties of Neurons

## Physical Properties of Membrane

The cell membrane is a lipid bilayer 3 to 4 nm thick.

- Insulating feature: impermeable to most charged molecules ( $C_m$ ).
- Highly selective (ion) channels ( $R_m$ ).

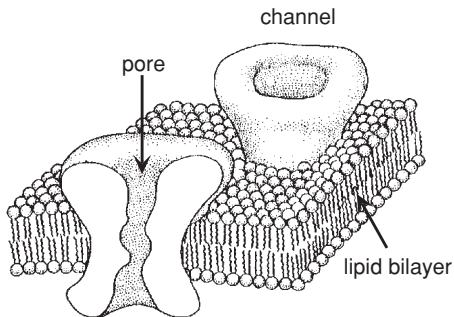


Figure 2: The cell membrane.

# Electrical Properties of Neurons

## Energy Conversion in the Membrane

Membrane potentials are small enough to allow neurons to take advantage of thermal energy to help transport ions across the membrane, but are large enough so that the thermal fluctuations do not swamp the signaling capabilities of the neurons.

The thermal energy is equal to the electric potential energy, i.e.,

$$RT = V_T F \quad (1)$$

where  $V_T$  is the membrane potential,  $T$  is the temperature;  $R$  is universal gas constant,  $F$  is Faraday's constant.

By (1), we have

$$V_T = \frac{RT}{F} \quad (2)$$

# Electrical Properties of Neurons

## Capacitor of a neuron

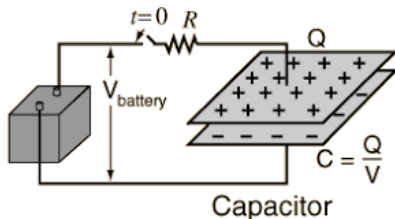


Figure 3: The capacitor: relation between the amount of charge and the voltage.

$$C_m V = Q \quad (3)$$

Taking the time derivative of (3) yields

$$C_m \frac{dV}{dt} = \frac{dQ}{dt} \quad (4)$$

# Electrical Properties of Neurons

## Resistance of a Neuron

According to the Ohm's law, the voltage deviation can be written by

$$\Delta V = I_e R_m(V) \quad (5)$$

where  $I_e$  is the injected current (from outside),  $R_m$  is the resistance, and  $\Delta V$  is the voltage deviation.

The conductance is defined by the reciprocal of the resistance

$$g_i(V) = \frac{1}{R_m(V)} \quad (6)$$

# Electrical Properties of Neurons

## Equilibrium and Reversal Potentials

The channels are heterogeneous.

Negative membrane potentials attract positive ions into the neuron and repel negative ions. In addition, ions diffuse through channels because the ion concentrations differ inside and outside the neuron.

By the Boltzmann distribution, the ratio of the active enough ions who can finish the energy conversion is  $e^{\frac{zE}{V_T}}$  under the temperature  $T$ . In a balance case, we have

$$[\text{outside}] = [\text{inside}]e^{\frac{zE}{V_T}} \quad (7)$$

$$E = \frac{V_T}{z} \ln \left( \frac{[\text{outside}]}{[\text{inside}]} \right) \quad (8)$$



# Electrical Properties of Neurons

## Equilibrium and Reversal Potentials

| ions      | equilibrium |
|-----------|-------------|
| $K^+$     | -90~-70 mV  |
| $Ca^{2+}$ | 150mV       |
| $Na^+$    | 50mV        |

Table 1: Equilibrium of various ions.

- $V < E$ :  $Ka^+$  will go from outside to inside to decrease the membrane potential
- $V > E$ :  $Na^+$  and  $Ca^{2+}$  will go from outside to inside to decrease the membrane potential.

# Single-Compartment Model

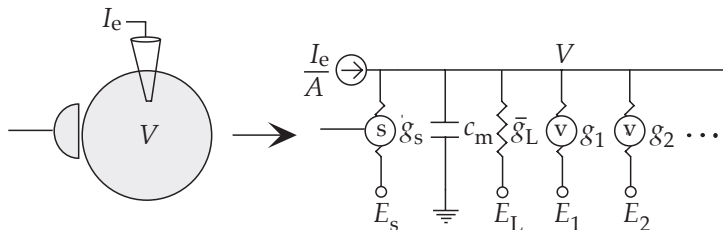


Figure 4: The equivalent circuit for a one-compartment neuron model.

Define  $c_m = \frac{C_m}{A}$  be the capacitor in the unit area. By the Kirchhoff law, we have

$$c_m \frac{dV}{dt} = -i_m + \frac{I_e}{A} \quad (9)$$

# Single-Compartment Model

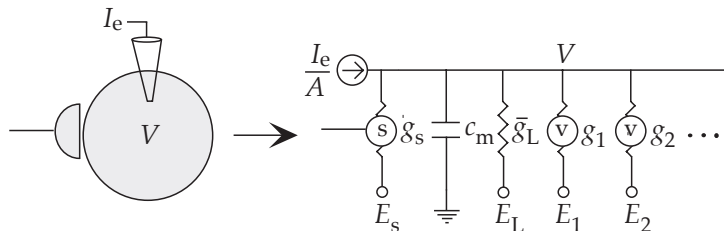


Figure 5: The equivalent circuit for a one-compartment neuron model.

$$i_m = \sum_i g_i(V - E_i) + \bar{g}_L(V - E_L)$$

$$\frac{dV(t)}{dt} = -\frac{1}{c_m} \left( \sum_i g_i + \bar{g}_L \right) V + \frac{1}{c_m} \left( \frac{I_e}{A} - \sum_i g_i E_i - \bar{g}_L E_L \right) \quad (10)$$

## The 2nd Model: Integrate-and-Fire Model

A neuron will fire an action potential when  $V \in [-55, -50]$ . In the following, we model the action potential.

To simplify, we let  $g_i = 0$ . Then, we have

$$c_m \frac{dV}{dt} = -\bar{g}_L(V - E_L) + \frac{I_e}{A} \quad (11)$$

Define  $r_m = R_m \cdot A$  be the unit resistance in the unit area and  $\tau_m = c_m r_m$  be a time constant. Multiplying  $r_m$  at both sides give

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I_e \quad (12)$$

## The 2nd Model: Integrate-And-Fire Model

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I_e$$

Solving (13) yields

$$V(t) = E_L + R_m I_e + (V(0) - E_L - R_m I_e) e^{-\frac{t}{\tau_m}} \quad (13)$$

Let  $V(0) = V_{\text{reset}}$  and  $t_{\text{isi}}$  be the time reach threshold. One can calculate  $t = t_{\text{isi}}$  by

$$V(t_{\text{isi}}) = V_{\text{th}} = E_L + R_m I_e + (V_{\text{reset}} - E_L - R_m I_e) e^{-\frac{t_{\text{isi}}}{\tau_m}} \quad (14)$$

Solving (14) gives the following **interspike-interval firing rate**

$$r_{\text{isi}} = \frac{1}{t_{\text{isi}}} = \begin{cases} \left( \tau_m \ln \left( \frac{R_m I_e + E_L - V_{\text{reset}}}{R_m I_e + E_L - V_{\text{th}}} \right) \right)^{-1}, & R_m I_e > V_{\text{th}} E_L \\ 0, & R_m I_e \leq V_{\text{th}} - E_L \end{cases}$$

# The 2nd Model: Integrate-And-Fire Model

## Spike-Rate Adaptation

When  $I_e$  is large enough, by the approximation  $\ln(x + 1) = x$ , one has

$$r_{\text{isi}} = \left[ \frac{R_m}{\tau_m(V_{\text{th}} - V_{\text{reset}})} I_e + \frac{E_L - V_{\text{th}}}{\tau_m(V_{\text{th}} - V_{\text{reset}})} \right]_+$$

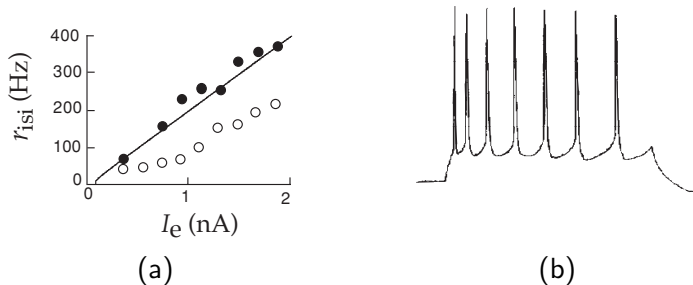


Figure 6: Data fitting performance of the interspike-interval firing rate.

# The 2nd Model: Integrate-And-Fire Model

## Spike-Rate Adaptation and Refractoriness

To model the spike-rate adaptation process, we add a term  $-r_m g_{\text{sra}}(V - E_K)$  in the model

$$\tau_m \frac{dV}{dt} = E_L - V - r_m g_{\text{sra}}(V - E_K) + R_m I_e \quad (15)$$

$$\tau_{\text{sra}} \frac{dg_{\text{sra}}}{dt} = -g_{\text{sra}} \quad (16)$$

where  $g_{\text{sra}}(t_k) = (\lim_{t \rightarrow t_k^-} g_{\text{sra}}(t)) + \Delta g_{\text{sra}}$ .

# The 2nd Model: Integrate-And-Fire Model

## Spike-Rate Adaptation and Refractoriness

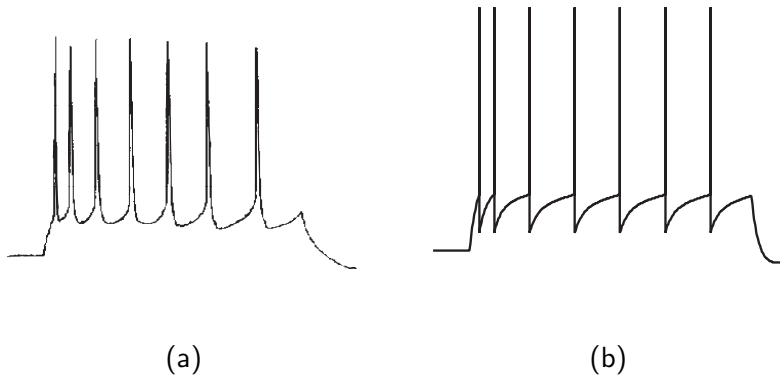


Figure 7: Estimated state trajectories.



# The 2nd Model: Integrate-And-Fire Model

## Voltage-Dependent Conductances

Most of the interesting properties arise from nonlinearities associated with active membrane conductances  $g_i$ .

$g_i$  depends on several factors

- 1 **voltage-dependent membrane conductances**
- 2 transmitter-dependent membrane conductances
- 3  $\text{Ca}^{2+}$ -dependent membrane conductances

Let  $g_i(t) = \bar{g}_i P_i(t)$  be the conductance at time  $t$ . The problem is that: how to model the dynamics of  $g_i(t)$  [or  $P_i(t)$ ]?

# The 2nd Model: Integrate-And-Fire Model

## Voltage-Dependent Conductances

How to model the dynamics of  $g_i(t)$  [or  $P_i(t)$ ]?

The voltage-dependent membrane conductances [ $g_i(t) = g_i(V(t))$ ] are divided into delayed-rectifier  $K^+$  conductance and fast  $Na^+$  conductance

Let  $n \in [0, 1]$  be the gating or activation variable. We can write

$$P_K = n^k \quad (17)$$

The dynamics of  $n$  can be written by

$$\frac{dn}{dt} = \alpha_n(V)(1 - n) - \beta_n(V)n \quad (18)$$

The key elements are the opening and closing rate  $\alpha_n(V)$  and  $\beta_n(V)$ .

## The 2nd Model: Integrate-And-Fire Model

$$\frac{dn}{dt} = \alpha_n(V)(1 - n) - \beta_n(V)n$$

Let  $\tau_n(V)$  and  $n_\infty(V)$  be defined by

$$\tau_n(V) = \frac{1}{\alpha_n(V) + \beta_n(V)} \quad (19)$$

$$n_\infty(V) = \frac{\alpha_n(V)}{\alpha_n(V) + \beta_n(V)} \quad (20)$$

We rewrite the dynamics of the  $n$  by

$$\tau_n(V) \frac{dn}{dt} = n_\infty(V) - n \quad (21)$$

# The 2nd Model: Integrate-And-Fire Model

## Voltage-Dependent Conductances

There are two ways to model the opening and closing rate

### ① Mechanism Model:

$$\alpha_n(V) = A_\alpha e^{-\frac{qB_\alpha}{k_B T}} = A_\alpha e^{-\frac{B_\alpha V}{V_T}}, \quad B_\alpha < 0 \quad (22)$$

$$\beta_n(V) = A_\beta e^{-\frac{qB_\beta}{k_B T}} = A_\beta e^{-\frac{B_\beta V}{V_T}} \quad (23)$$

### ② Data Fitting Model:

$$\alpha_n(V) = \frac{0.01(V + 55)}{1 - e^{-0.1(V+55)}} \quad (24)$$

$$\beta_n(V) = 0.125e^{-0.0125(V+65)} \quad (25)$$

# The 2nd Model: Integrate-And-Fire Model

## Voltage-Dependent Conductances

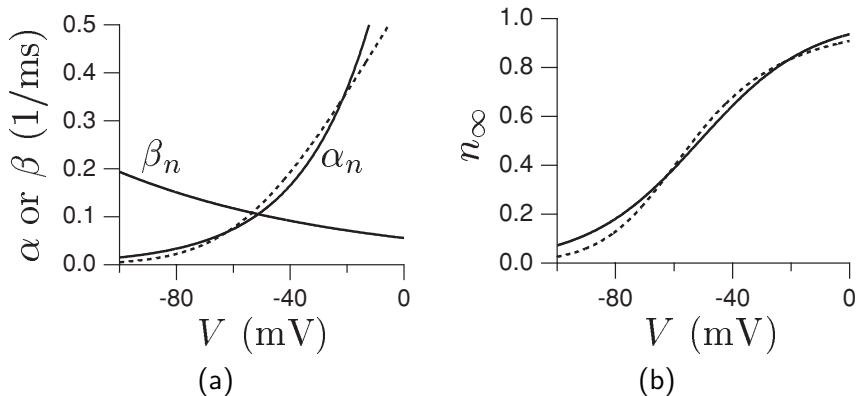


Figure 8: Estimated state trajectories.

# The 2nd Model: Integrate-And-Fire Model

## Transient Conductances

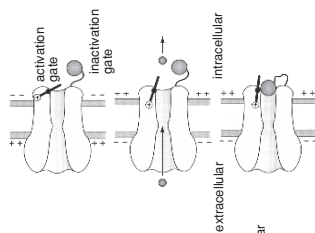


Figure 9: Transient Conductances.

The probability of the opening channels is

$$P_{\text{Na}} = m^k h \quad (26)$$

where  $m$  is an activation variable and  $h$  is the probability that the ball does not block the channel pore.

# The 2nd Model: Integrate-And-Fire Model

## Transient Conductances

We can do the same things for  $\alpha_m$ ,  $\beta_m$ ,  $\alpha_h$  and  $\beta_h$  as  $\alpha_n(V)$  and  $\beta_n(V)$ .

### 1 Mechanism Model

$$\alpha_m(V) = \bar{A}_\alpha e^{-\frac{q\bar{B}_\alpha}{k_B T}} = \bar{A}_\alpha e^{-\frac{\bar{B}_\alpha V}{V_T}}, \quad \beta_m(V) = \bar{A}_\beta e^{-\frac{q\bar{B}_\beta}{k_B T}} = \bar{A}_\beta e^{-\frac{\bar{B}_\beta V}{V_T}}$$
$$\alpha_h(V) = \tilde{A}_\alpha e^{-\frac{q\tilde{B}_\alpha}{k_B T}} = \tilde{A}_\alpha e^{-\frac{\tilde{B}_\alpha V}{V_T}}, \quad \beta_h(V) = \tilde{A}_\beta e^{-\frac{q\tilde{B}_\beta}{k_B T}} = \tilde{A}_\beta e^{-\frac{\tilde{B}_\beta V}{V_T}}$$

### 2 Data Fitting Model

$$\alpha_m = \frac{0.1(V + 40)}{1 - e^{-0.1(V+40)}}, \quad \beta_m = 4e^{-0.0556(V+65)},$$
$$\alpha_h = 0.07e^{-0.05(V+65)}, \quad \beta_h = \frac{1}{1 + e^{-0.1(V+35)}}$$

- 1 The membrane can be modelled by the capacitor, resistance, and the amount of active (enough) ions can be calculated by Boltzmann distribution.
- 2 Single-Compartment model is the simplest model by the Kirchhoff's laws.
- 3 Integrate-and-Fire improves single-compartment in two aspects: spike-rate adaptation, time-varying voltage-dependent conductances.



Thank you for your listening!