Nonlinear Integrate-and-Fire Model



Neuronal Dynamics: Computational Neuroscience of Single Neurons

Week 1 and Week 4:

- **Nonlinear Integrate-and-fire Model**
- Wulfram Gerstner
- EPFL, Lausanne, Switzerland



Nonlinear Integrate-and-fire (NLIF) - Definition

- quadratic and expon. IF

- Extracting NLIF model from data

- exponential Integrate-and-fire

- Extracting NLIF from detailed model

- from two to one dimension

- Quality of NLIF?

Neuronal Dynamics – Review: Nonlinear Integrate-and Fire

LIF (Leaky integrate-and-fire) $\tau \cdot \frac{d}{dt}u = -(u - u_{rest}) + RI(t)$

NLIF (nonlinear integrate-and-fire)

$$\tau \cdot \frac{d}{dt}u = F(u) + RI(t)$$

If firing:

$$u \rightarrow u_{reset}$$



Neuronal Dynamics – 1.4. Leaky Integrate-and Fire revisited





Neuronal Dynamics – 1.4. Nonlinear Integrate-and Fire

 $\frac{d}{dt}u$

Nonlinear Integrate-and-Fire NLIF

$$\tau \cdot \frac{d}{dt}u = F(u) + RI(t)$$

firing: if $u(t) = \theta_r$ then

$$\mathcal{U} \longrightarrow \mathcal{U}_r$$





$$\tau \cdot \frac{d}{dt}u = F(u) + RI(t)$$
 NON
if $u(t) = \theta_r$ then Fire+reset three

Nlinear

shold

Nonlinear Integrate-and-fire Model



$$\tau \cdot \frac{u}{dt} u = F(u) + RI(t)$$
 NON
if $u(t) = \theta_r$ then Fire+reset three

Nonlinear Integrate-and-fire Model





Nonlinear Integrate-and-Fire Model



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Neuronal Dynamics – Review: Nonlinear Integrate-and-fire



Neuronal Dynamics – Review: Nonlinear Integrate-and-fire

(1)
$$\tau \frac{du}{dt} = f(u) + RI(t)$$
(2) If $u = \theta_{rese}$

What is a good choice of f?

(i) Extract f from data

(ii) Extract f from more complex models

_{et} then reset to $u = u_r$

Neuronal Dynamics – 1.5. Inject current – record voltage



Neuronal Dynamics – Inject current – record voltage



Badel et al., J. Neurophysiology 2008

Neuronal Dynamics – Review: Nonlinear Integrate-and-fire



$$\frac{u}{dt} = -(u - u_{rest}) + \Delta \exp(\frac{u - \vartheta}{\Delta})$$

Neuronal Dynamics – Review: Nonlinear Integrate-and-fire

(1)
$$\tau \frac{du}{dt} = f(u)$$

(2) If $u = \theta$

Best choice of *f* : linear + exponential

BUT: Limitations – need to add

- -Adaptation on slower time scales
- -Possibility for a diversity of firing patterns
- -Increased threshold \mathcal{G} after each spike -Noise

+RI(t)

 V_{reset} then reset to $u = u_r$

 $\tau \frac{du}{dt} = -(u - u_{rest}) + \Delta \exp(\frac{u - \vartheta}{\Lambda})$

Week 4 – part 5: Nonlinear Integrate-and-Fire Model



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Neuronal Dynamics – 4.5. Further reduction to 1 dimension

After reduction of HH to two dimensions:

2-dimensional equation stimulus

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w) \qquad \text{slow!}$$

Separation of time scales -w is nearly constant (most of the time)

Neuronal Dynamics – 4.5 sparse activity in vivo

Spontaneous activity in vivo



-spikes are rare events -membrane potential fluctuates around 'rest' Aims of Modeling: - predict spike initation times

awake mouse, cortex, freely whisking,

Crochet et al., 2011

- predict subthreshold voltage

Neuronal Dynamics – 4.5. Further reduction to 1 dimension

stimulus

$$\tau \frac{du}{dt} = F(u, w) + I(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Separation of time scales

$$au_w >> au_u$$

→ Flux nearly horizontal



Neuronal Dynamics – 4.5. Further reduction to 1 dimension

Hodgkin-Huxley reduced to 2dim

$$\tau \frac{du}{dt} = F(u, w) + I(t)$$

$$\tau_{w} \frac{dw}{dt} = G(u, w)$$

$$\Im = 1$$

Separation of time scales

$$\tau_{w} \rightarrow \tau_{u}$$

$$\tau_{w} \frac{dw}{dt} \approx 0 \rightarrow w \approx w_{rest}$$

$$\tau \frac{du}{dt} = F(u, w_{rest}) + RI(t)$$



Stable fixed point

0

-1

Neuronal Dynamics – Review: Nonlinear Integrate-and-fire

(i) Extract f from more complex models



See week 3: 2dim version of Hodgkin-Huxley

 $\tau \frac{du}{dt} = F(u, w) + RI(t)$ $\tau_w \frac{dw}{dt}$ =G(u,w)

models $\tau \frac{du}{dt} = f(u) + RI(t)$

A. detect spike and reset resting state

Separation of time scales: Arrows are nearly horizontal

Spike initiation, from rest RI(t) $W \approx W_{rest}$

B. Assume *W*=*W*rest

Neuronal Dynamics – Review: Nonlinear Integrate-and-fire



Neuronal Dynamics – 4.5. Nonlinear Integrate-and-Fire Model



$$\tau \frac{du}{dt} = F(u, w_{rest}) + RI(t) = f(u) + RI(t)$$

$$\rightarrow \text{Nonlinear I&F (see week)$$



Image: Neuronal Dynamics, Gerstner et al., Cambridge Univ. Press (2014)

ek 1!)

Neuronal Dynamics – 4.5. Nonlinear Integrate-and-Fire Model

Exponential integrate-and-fire model (EIF)

$$f(u) = -(u - u_{rest}) + \Delta \exp(\frac{u - \vartheta}{\Delta})$$

$$\tau \frac{du}{dt} = F(u, w_{rest}) + RI(t) = f(u) + RI(t)$$

$$\rightarrow \text{Nonlinear I&F (see week)}$$



Image: Neuronal Dynamics, Gerstner et al., Cambridge Univ. Press (2014)

ek 1!)

Neuronal Dynamics – 4.5. Exponential Integrate-and-Fire Model

Exponential integrate-and-fire model (EIF)

$$f(u) = -(u - u_{rest}) + \Delta \exp(\frac{u - \vartheta}{\Delta})$$



Image: Neuronal Dynamics, Gerstner et al., Cambridge Univ. Press (2014)

Neuronal Dynamics – 4.5. Exponential Integrate-and-Fire Model

Direct derivation from Hodgkin-Huxley

$$C\frac{du}{dt} = -g_{Na} m^{3} h(u - E_{Na}) - g_{K} n^{4} (u - E_{K}) - g_{l} (u - E_{l}) + I(t)$$

$$C\frac{du}{dt} = -g_{Na}[m_0(u)]^3 h_{rest}(u - E_{Na}) - g_K[n_{rest}]^4(u - E_K) - g_l(u - E_l) + I(t)$$

$$\tau \frac{du}{dt} = F(u, h_{rest}, n_{rest}) + RI(t) = f(u) + RI(t)$$

Fourcaud-Trocme et al, J. Neurosci. 2003

$$f(u) = -(u - u_{rest}) + \Delta \exp(\frac{u - \vartheta}{\Delta})$$

gives expon. I&F

Neuronal Dynamics – 4.5. Nonlinear Integrate-and-Fire Model



2-dimensional equation

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Separation of time scales -w is constant (if not firing) $\tau \frac{du}{dt} = f(u) + RI(t)$ threshold+reset for firing

Neuronal Dynamics – 4.5. Nonlinear Integrate-and-Fire Model

2-dimensional equation

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Separation of time scales -w is constant (if not firing) $\tau \frac{du}{dt} = f(u) + RI(t)$ Linear plus exponential

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awake mouse, cortex, freely whisking,

Crochet et al., 2011

- predict subthreshold voltage

Neuronal Dynamics – 4.5. How good are integrate-and-fire models?



Aims: - predict spike initation times - predict subthreshold voltage

Badel et al., 2008

Add adaptation and refractoriness (week 7)

Neuronal Dynamics – Quiz 4.7.

A. Exponential integrate-and-fire model.

The model can be derived

[] from a 2-dimensional model, assuming that the auxiliary variable w is constant.
[] from the HH model, assuming that the gating variables h and n are constant.
[] from the HH model, assuming that the gating variables m is constant.
[] from the HH model, assuming that the gating variables m is instantaneous.

B. Reset.

[] In a 2-dimensional model, the auxiliary variable w is necessary to implement a reset of the voltage after a spike
[] In a nonlinear integrate-and-fire model, the auxiliary variable w is necessary to implement a reset of the voltage after a spike
[] In a nonlinear integrate-and-fire model, a reset of the voltage after a spike is implemented algorithmically/explicitly

Neuronal Dynamics – Nonlinear Integrate-and-Fire

Reading: W. Gerstner, W.M. Kistler, R. Naud and L. Paninski, Neuronal Dynamics: from single neurons to networks and models of cognition. Chapter 4: Introduction. Cambridge Univ. Press, 2014 OR W. Gerstner and W.M. Kistler, Spiking Neuron Models, Ch.3. Cambridge 2002 OR J. Rinzel and G.B. Ermentrout, (1989). Analysis of neuronal excitability and oscillations. In Koch, C. Segev, I., editors, *Methods in neuronal modeling*. MIT Press, Cambridge, MA.

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- -Fourcaud-Trocme, N., Hansel, D., van Vreeswijk, C., and Brunel, N. (2003). How spike generation mechanisms determine the neuronal response to fluctuating input. J. Neuroscience, 23:11628-11640.
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