

Fundamentals of Computational Neuroscience 2e

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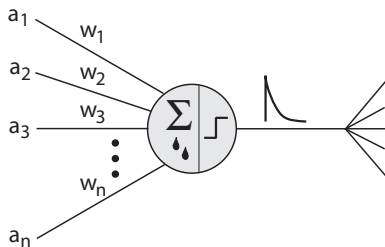
Chapter 3: Simplified neuron and population models

The leaky integrate-and-fire neuron

$$\tau_m \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t), \quad (1)$$

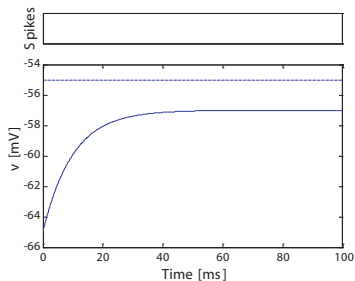
$$v(t^f) = \vartheta. \quad (2)$$

$$\lim_{\delta \rightarrow 0} v(t^f + \delta) = v_{\text{res}}, \quad (3)$$

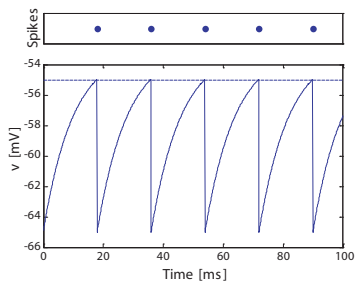


The leaky integrate-and-fire neuron (cont.)

A. External input $RI_{\text{ext}} = 8\text{mV} < \text{threshold}$



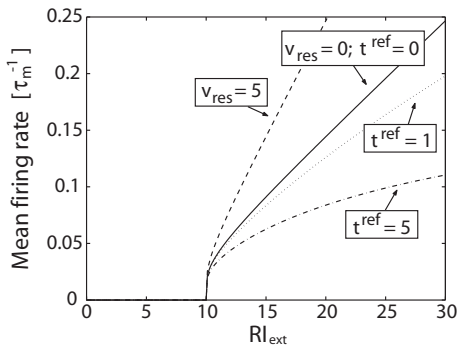
B. External input $RI_{\text{ext}} = 12\text{mV} > \text{threshold}$



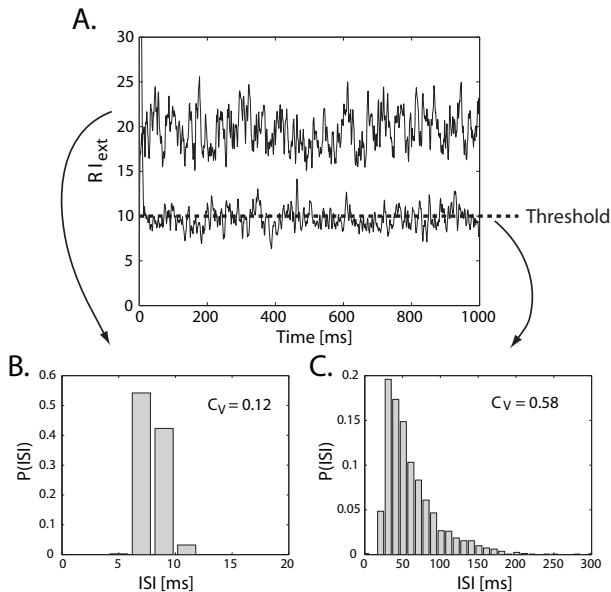
The LIF-neuron (cont.): Gain function

The inverse of the first passage time defines the **firing rate**

$$\bar{r} = \left(t^{\text{ref}} - \tau_m \ln \frac{\vartheta - RI}{v_{\text{res}} - RI} \right)^{-1} \quad (4)$$



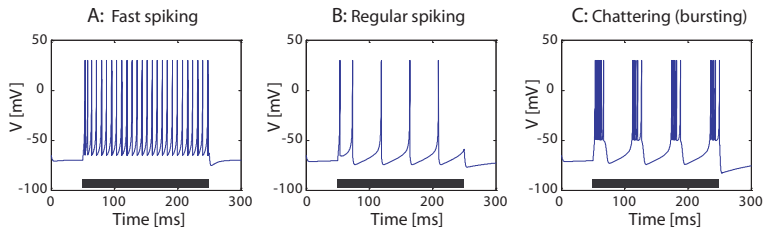
The LIF-neuron (cont.): Noise



The Izhikevich neuron

$$\frac{dv(t)}{dt} = 0.04v^2(t) + 5v(t) + 140 - u + I(t)$$
$$\frac{du(t)}{dt} = a(bv - u)$$

$$v(v > 30) = c \text{ and } u(v > 30) = u - d$$



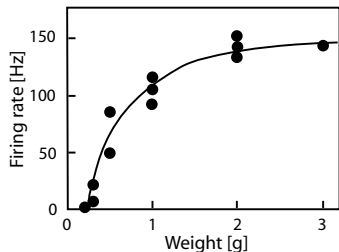
McCulloch-Pitts neuron

$$h = \sum_i x_i^{\text{in}}$$

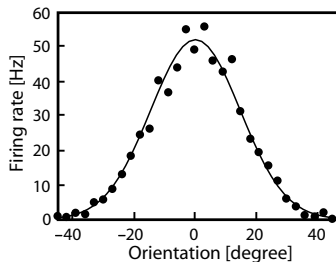
$$x^{\text{out}} = \begin{cases} 1 & \text{if } h > \Theta \\ 0 & \text{otherwise} \end{cases}$$

The firing rate hypothesis

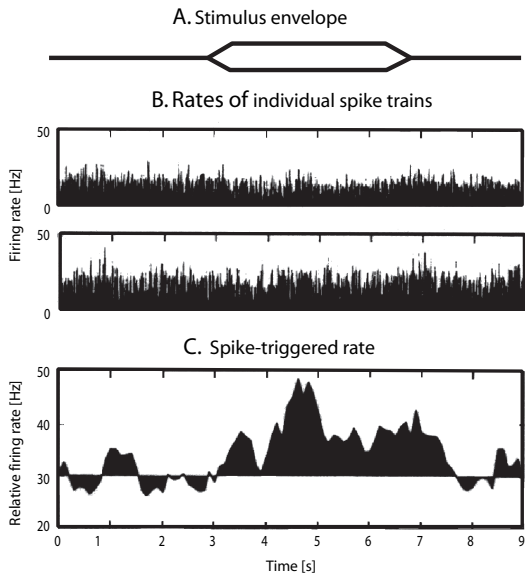
A. Stretch receptor on frog muscle



B. Tuning curve of V1 neuron in cat

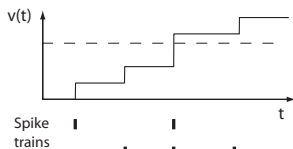


Counter example: correlation code (?)

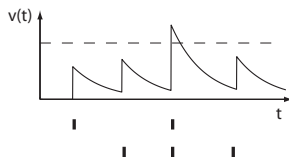


Coincidence detector

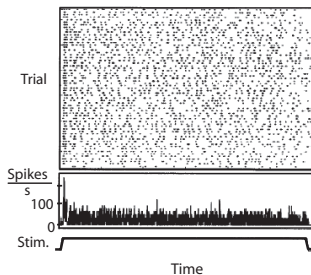
A. Perfect integrator



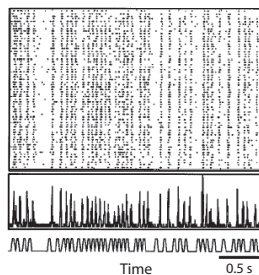
B. Coincidence detector



A. Constant stimulus

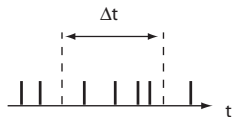


B. Rapidly changing stimulus

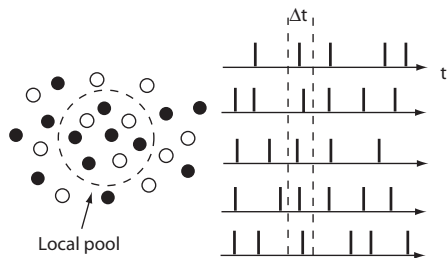


Population model

A. Firing rate in one spike train



B. Population rate



Population dynamics

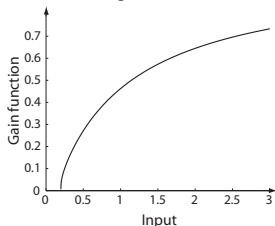
For slow varying input (adiabatic limit), when all nodes do practically the same, same input, etc (Wilson and Cowan, 1972):

$$\tau \frac{dA(t)}{dt} = -A(t) + g(RI^{\text{ext}}(t)). \quad (5)$$

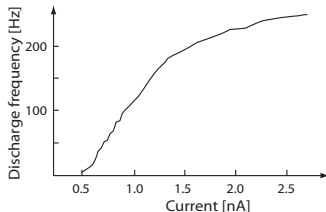
Gain function:

$$g(x) = \frac{1}{t^{\text{ref}} - \tau \log(1 - \frac{1}{\tau x})}, \quad (6)$$






A. Gain function for population average in adiabatic limit



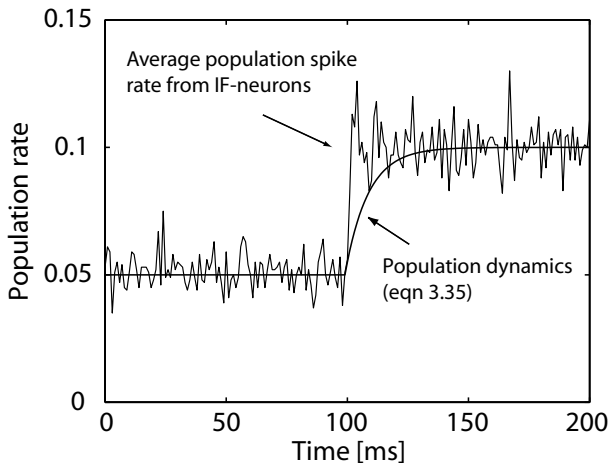
B. Gain function of hippocampal pyramidal neuron



Other gain functions

Type of function	Graphical represent.	Mathematical formula	Matlab implementation
Linear		$g^{\text{lin}}(x) = x$	x
Step		$g^{\text{step}}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{elsewhere} \end{cases}$	<code>floor(0.5*(1+sign(x)))</code>
Threshold-linear		$g^{\text{theta}}(x) = x \Theta(x)$	<code>x.*floor(0.5*(1+sign(x)))</code>
Sigmoid		$g^{\text{sig}}(x) = \frac{1}{1+\exp(-x)}$	<code>1./(1+exp(-x))</code>
Radial-basis		$g^{\text{gauss}}(x) = \exp(-x^2)$	<code>exp(-x.^2)</code>

Fast population response!!!



Further Readings

- Wolfgang Maass and Christopher M. Bishop (eds.) (1999), **Pulsed neural networks**, MIT Press.
- Wulfram Gerstner (2000), **Population dynamics of spiking neurons: fast transients, asynchronous states, and locking**, in **Neural Computation** 12: 43–89.
- Eugene M. Izhikevich (2003), **Simple Model of Spiking Neurons**, in **IEEE Transactions on Neural Networks**, 14: 1569–1072.
- Eugene M. Izhikevich (2004), **Which model to use for cortical spiking neurons?**, in **IEEE Transactions on Neural Networks**, 15: 1063–1070.
- Warren McCulloch and Walter Pitts (1943) **A logical calculus of the ideas immanent in nervous activity**, in **Bulletin of Mathematical Biophysics** 7:115–133.
- Huge R. Wilson and Jack D. Cowan (1972), **Excitatory and inhibitory interactions in localized populations of model neurons**, in **Biophys. J.** 12:1–24.
- Nicolas Brunel and Xiao-Jing Wang, (2001), **Effects of neuromodulation in a cortical network model of working memory dominated by recurrent inhibition**, in **Journal of Computational Neuroscience** 11: 63–85.