Fundamentals of Computational Neuroscience 2e

December 28, 2009

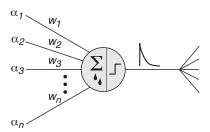
Chapter 3: Simplified neuron and population models

The leaky integrate-and-fire neuron

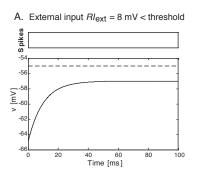
$$\tau_{\rm m} \frac{\mathrm{d}v(t)}{\mathrm{d}t} = -(v(t) - E_L) + RI(t), \tag{1}$$

$$v(t^{\mathbf{f}}) = \vartheta. \tag{2}$$

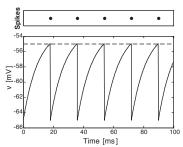
$$\lim_{\delta \to 0} v(t^{\rm f} + \delta) = v_{\rm res},\tag{3}$$



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



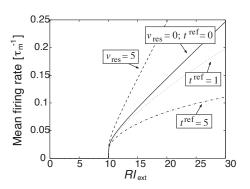
B. External input RI ext= 12 mV > threshold



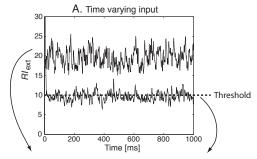
The LIF-neuron (cont.): Gain function

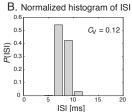
The inverse of the first passage time defines the firing rate

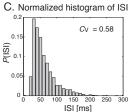
$$\bar{r} = (t^{\text{ref}} - \tau_{\text{m}} \ln \frac{\vartheta - RI}{v_{\text{res}} - RI})^{-1}$$
(4)



The LIF-neuron (cont.): Noise





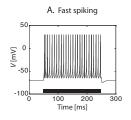


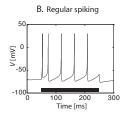
The Izhikevich neuron

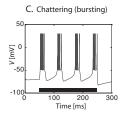
$$\frac{\mathrm{d}v(t)}{\mathrm{d}t} = 0.04v^2 + 5v + 140 - u + I(t)$$

$$\frac{\mathrm{d}u(t)}{\mathrm{d}t} = a(bv - u)$$

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







McCulloch-Pitts neuron

$$h = \sum_{i} x_{i}^{\text{in}}$$
 $x^{\text{out}} = \left\{ egin{array}{ll} 1 & ext{if } h > \Theta \ 0 & ext{otherwise} \end{array}
ight.$

BULLETIN OF MATHEMATICAL BIOPHYSICS VOLUME 5, 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

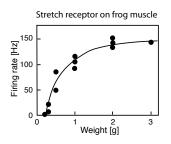
WARREN S. MCCULLOCH AND WALTER PITTS

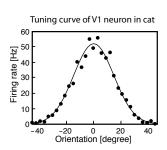
FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE, DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INS. AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, r events and the relations among them can be treated by means of p sitional logic. It is found that the behavior of every net can be desc in these terms, with the addition of more complicated logical mear nets containing circles; and that for any logical expression satis

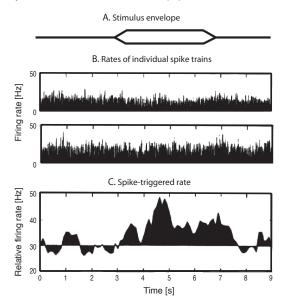


The firing rate hypothesis

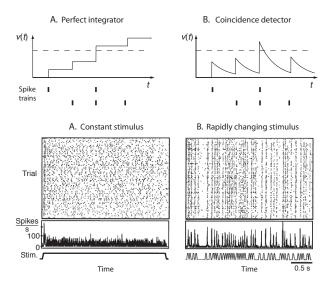




Counter example: correlation code (?)

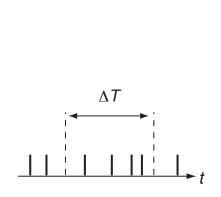


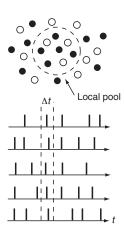
Integrator or coincidence detector?





Population model





Population dynamics

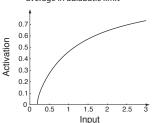
For slow varying input (adiabatic limit), when all nodes do practically the same, same input, etc (Wilson and Cowan, 1972):

$$\tau \frac{\mathrm{d}A(t)}{\mathrm{d}t} = -A(t) + g(RI^{\mathrm{ext}}(t)). \tag{5}$$

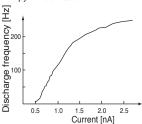
Gain function:

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

A. Activation function for population average in adiabatic limit



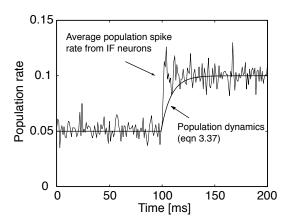
B. Activation function of hippocampal pyramidal neuron



Other gain functions

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

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, inBulletin 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.