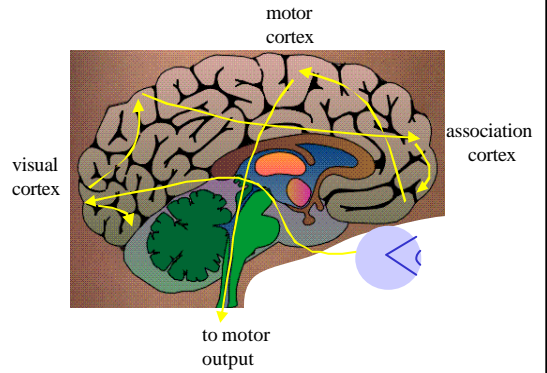


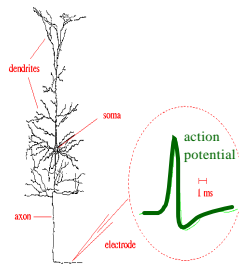
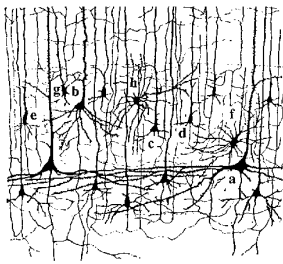
Introduction to computational neuroscience.
 Doctoral school Oct-Nov 2006

Wulfram Gerstner
<http://diwww.epfl.ch/w3mantra/>

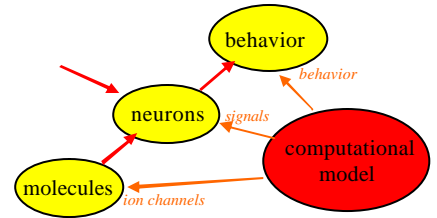


1 mm
 10 000 neurons
 3 km wires

Signal:
 action potential (spike)

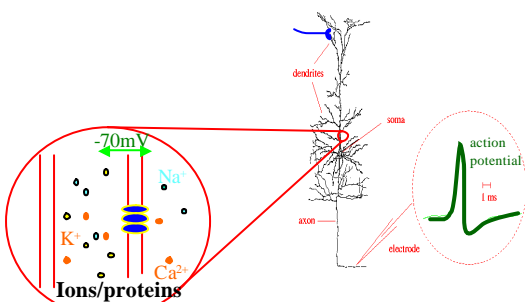


Computational Neuroscience

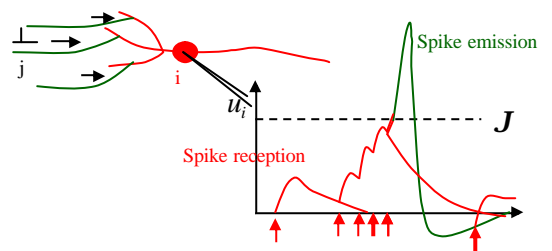


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Hodgkin-Huxley type models

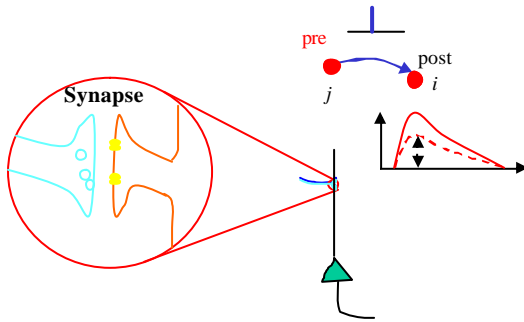


Integrate-and-fire type models

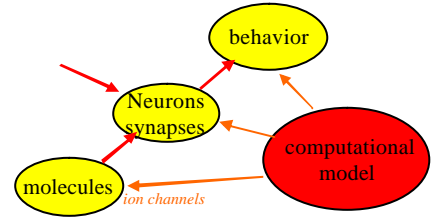


- spikes are events
- threshold
- spike/reset/refractoriness

Models of synaptic Plasticity



Computational Neuroscience



LCN Ecole Polytechnique Fédérale de Lausanne, EPFL
Laboratory of Computational Neuroscience, LCN, CH 1015 Lausanne

Introduction to computational neuroscience

- Lecture 1: Passive membrane and Integrate-and-Fire model
- Lecture 2: Hodgkin-Huxley models (detailed models)
- Lecture 3: Two-dimensional models (FitzHugh Nagumo)
- Lecture 4: synaptic plasticity
- Lecture 5: noise, network dynamics, associative memory

Wulfram Gerstner
<http://diwww.epfl.ch/w3mantra/>

Background: What is brain-style computation?



Brain

Computer



Systems for computing and information processing

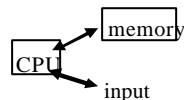


Brain

Computer



Distributed architecture
(10^{10} proc. Elements/neurons)
No separation of processing and memory



Von Neumann architecture
1 CPU
(10^{10} transistors)

Systems for computing and information processing



Brain

Computer



slow

Tasks:
Mathematical
 $\sqrt{5} \cos\left(\frac{7p}{5}\right)$

fast

fast

Real world
E.g. complex scenes

slow

Systems for computing and information processing



Brain



Computer

Where is the program?

Clear separation:
software (program)/hardware

Where is the memory?

Clear separation:
memory/processing

In the synaptic connections

Introduction to computational neuroscience

Lecture 1: Passive membrane and Integrate-and-Fire model

Lecture 2: Hodgkin-Huxley models (detailed models)

Lecture 3: Two-dimensional models (FitzHugh Nagumo)

Lecture 4: synaptic plasticity

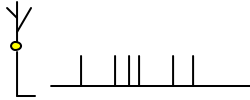
Lecture 5: noise, network dynamics, associative memory

Wulfram Gerstner

<http://diwww.epfl.ch/w3mantra/>

Why spiking neuron models?

Spikes versus rates



The Problem of Neuronal Coding

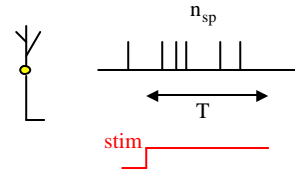
Book: Spiking Neuron Models

Chapter 1.4

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The Problem of Neuronal Coding



$$\text{Rate } n = \frac{n_{sp}(t; t+T)}{T}$$

Rate defined as temporal average

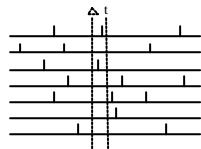
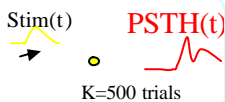
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The Problem of Neuronal Coding

Rate defined as average over stimulus repetitions

Peri-Stimulus Time Histogram



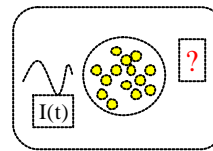
$$PSTH(t) = \frac{n(t; t + \Delta t)}{K \Delta t}$$

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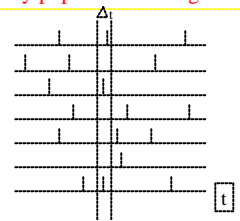
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The problem of neural coding:

population activity - rate defined by population average



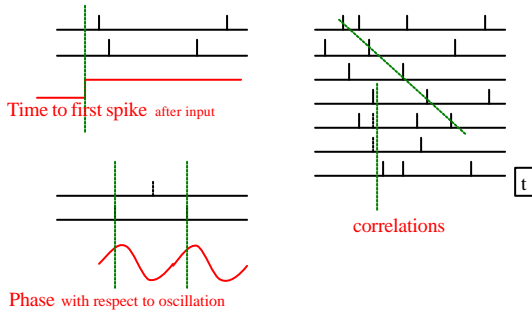
population dynamics?



population activity

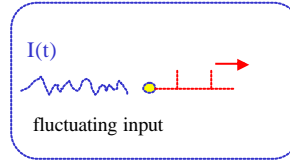
$$A(t) = \frac{n(t; t + \Delta t)}{N \Delta t}$$

The problem of neural coding:
temporal codes



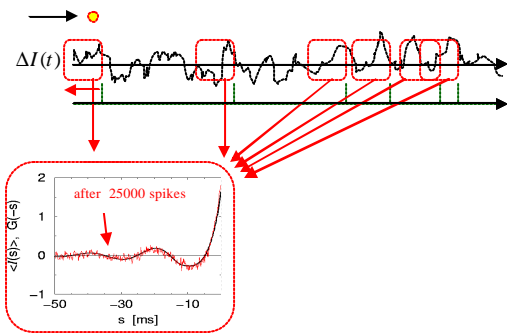
Relevance of temporal aspects-1

Reverse Correlations



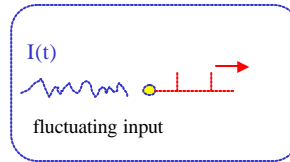
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Reverse-Correlation Experiments (simulations)



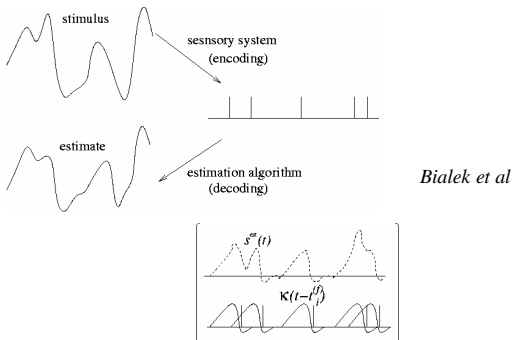
Relevance of temporal aspects-2

Stimulus Reconstruction



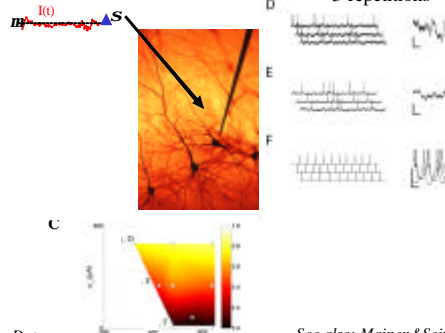
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Stimulus Reconstruction



Relevance of temporal aspects-3

Intrinsic reliability of neurons 3 repetitions



Exp. Data:
A. Rauch, H. Lüscher, U. Berne

See also: Mainen & Sejnowski

If we want to avoid prior assumptions about neural coding, we need to model neurons on the level of action potentials:

spiking neuron models

Introduction to computational neuroscience

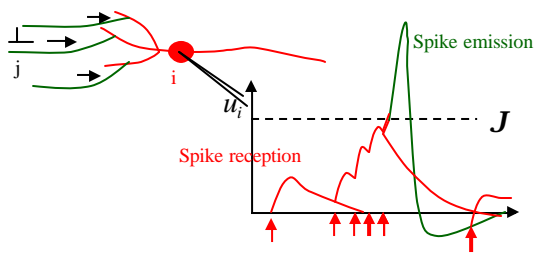
Lecture 1:

Passive membrane and Integrate-and-Fire model

- ✓ -The problem of neural coding
- The passive membrane
- Leaky integrate-and-fire model
- Generalized integrate-and-fire model
- Quality of integrate-and-fire models
- Coding revisited

Wulfram Gerstner
<http://diwww.epfl.ch/w3mantra/>

Integrate-and-fire type models



- spikes are events
- threshold
- spike/reset/refractoriness

Subthreshold regime

- linear
- passive membrane

Introduction to computational neuroscience

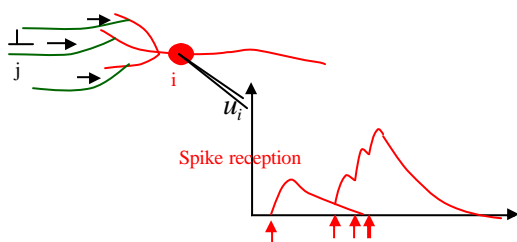
Lecture 1:

Passive membrane and Integrate-and-Fire model

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Wulfram Gerstner
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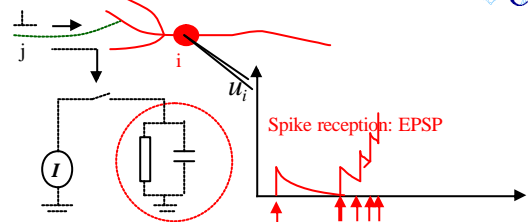
Subthreshold regime – passive membrane



Subthreshold regime

- linear
- passive membrane

Passive Membrane Model



Passive Membrane Model

Time-dependent input

$I(t)$

u

Blackboard:
Derive equation

Passive Membrane Model

I

u_i

Blackboard:
Voltage scale

$$t \cdot \frac{d}{dt} u = -(u - u_{rest}) + RI(t)$$

$$t \cdot \frac{d}{dt} V = -V + RI(t); \quad V = (u - u_{rest})$$

Passive Membrane

I

u_i

u_{rest}

Free solution: exponential decay

Start at t_0 with u

Blackboard:
free solution

$$t \cdot \frac{d}{dt} u = -(u - u_{rest});$$

$$u(t) = u_{rest} + (u_0 - u_{rest}) \exp\left(-\frac{t - t_0}{\tau}\right)$$

Passive Membrane Model-now exercises

$I(t)$

u_i

Step current input:

linear

$$t \cdot \frac{d}{dt} u = -(u - u_{rest}) + RI(t)$$

Passive Membrane Model-now exercises

I

u_i

impulse reception: impulse response function

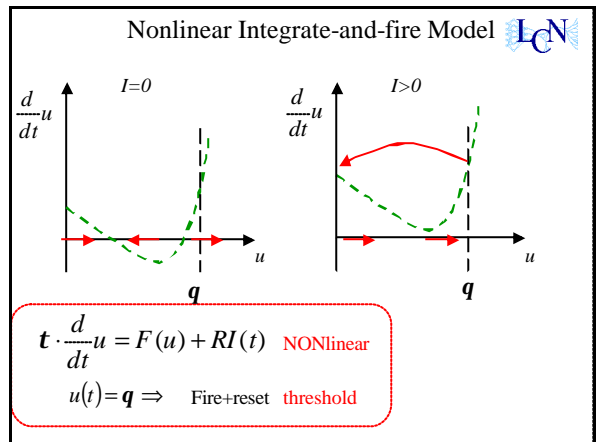
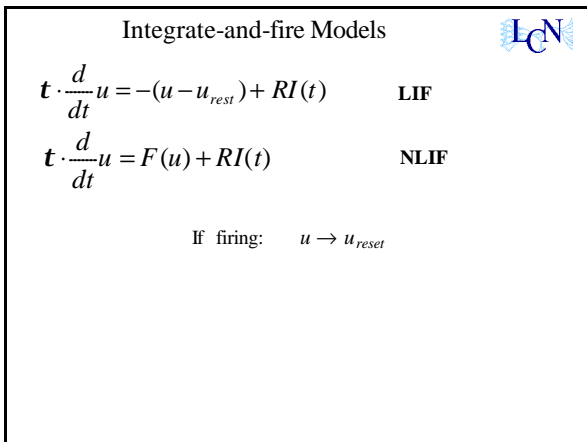
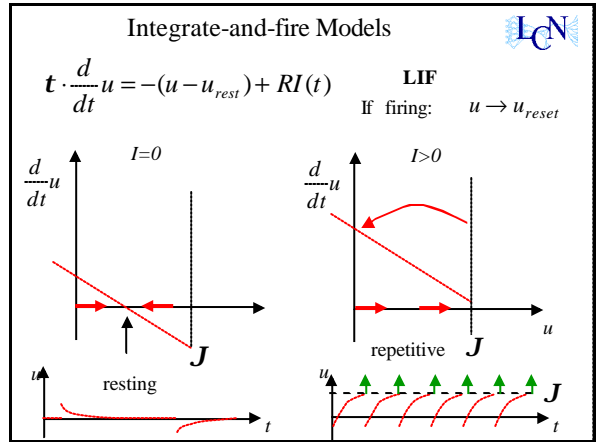
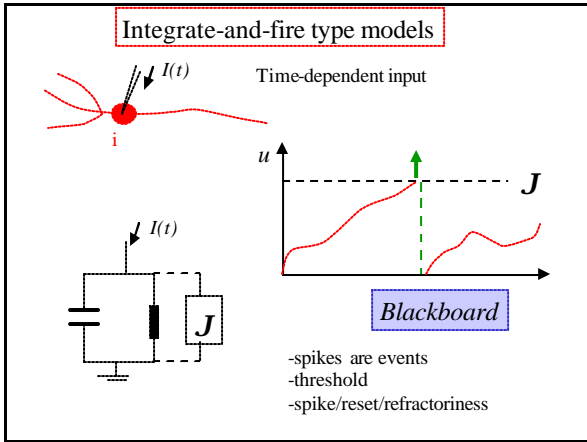
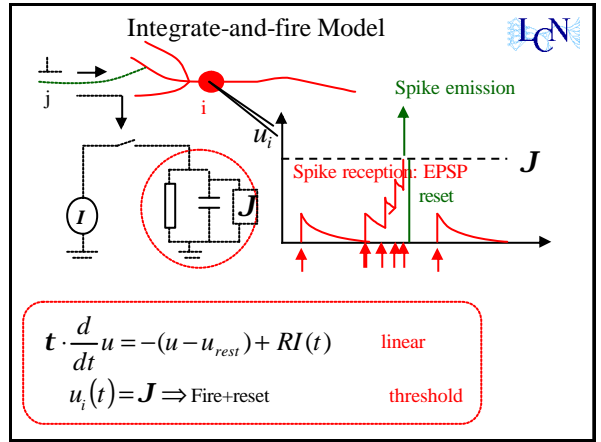
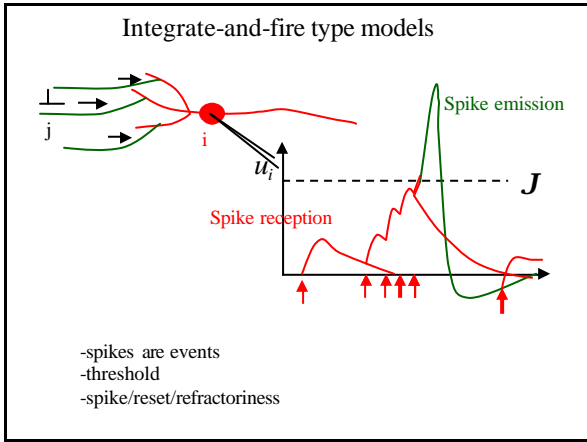
linear

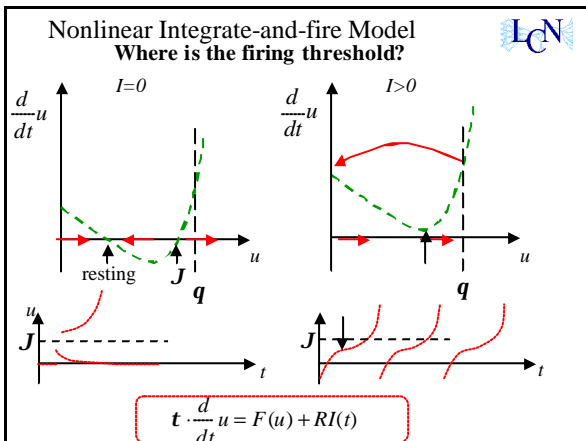
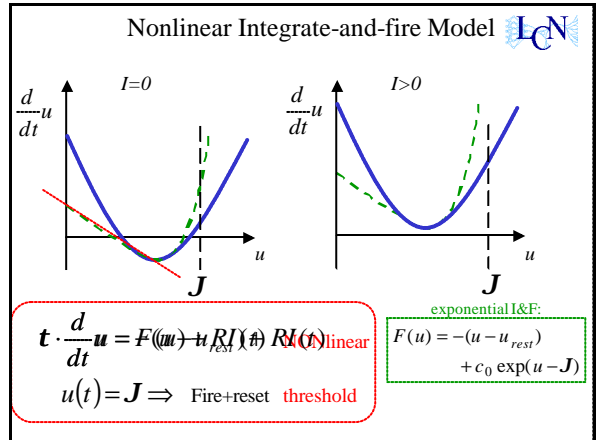
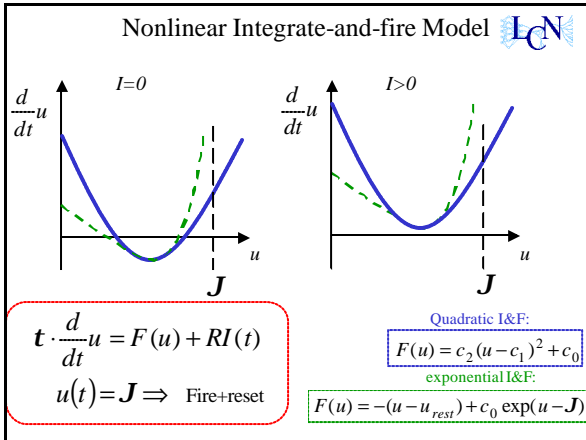
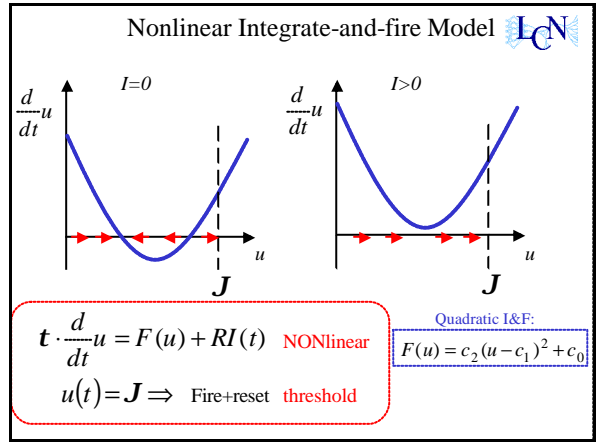
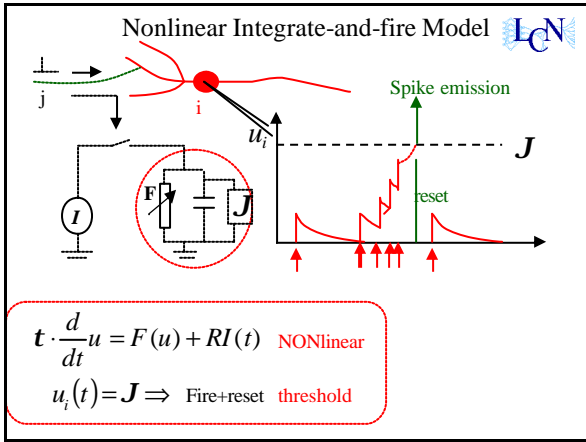
$$t \cdot \frac{d}{dt} u = -(u - u_{rest}) + RI(t)$$

Chapter 4: Formal Spiking models
Integrate-and-Fire model

BOOK: Spiking Neuron Models,
W. Gerstner and W. Kistler
Cambridge University Press, 2002

Chapter 4





Integrate-and Fire type models

Where is the firing threshold?

Leaky integrate-and-fire (LIF)

Strict voltage threshold

- by construction
- spike threshold = reset condition

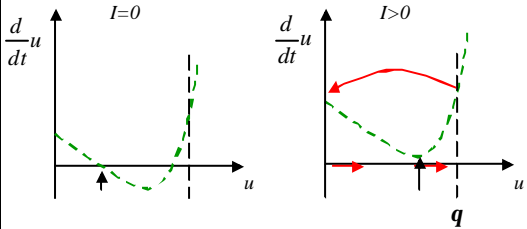
Nonlinear integrate-and-fire (eIF)

There is no strict firing threshold

- firing depends on input
- exact reset condition of minor relevance

Nonlinear Integrate-and-fire Model

Where is the firing threshold?



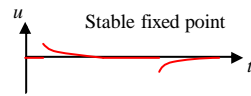
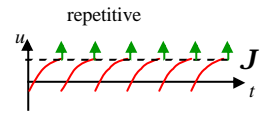
Exercises 2+3 now!

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

Leaky Integrate-and-fire Model

$$t \cdot \frac{d}{dt} u = -(u - u_{rest}) + RI_0$$

If firing: $u \rightarrow u_{reset}$



What is the firing rate?
 $f = g(I)$
Exercise 2+3 now!

Integrate-and Fire type models

Leaky integrate-and-fire (LIF)

Strict voltage threshold



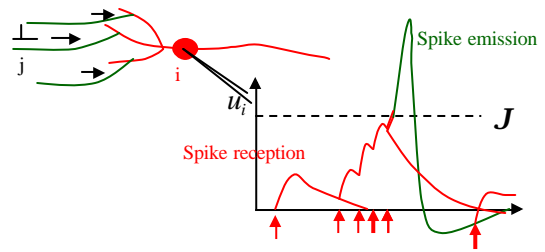
Nonlinear integrate-and-fire

no strict firing threshold

Spike Response Model (SRM)

Includes refractoriness

Integrate-and-fire type models

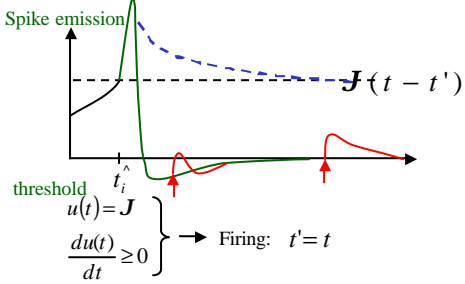


- spikes are events
- threshold
- spike/reset/refractoriness

Subthreshold regime

- linear
- passive membrane

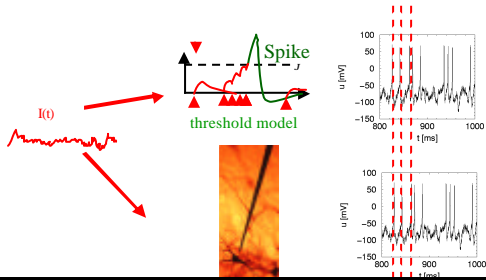
Spike Response Model and refractoriness



Integrate & Fire: Where is the firing threshold?

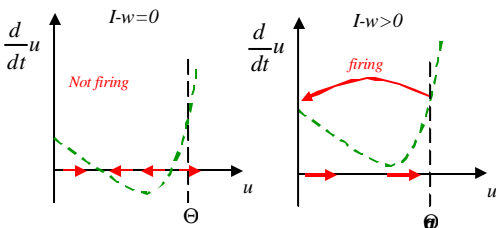
- ✓ 1: Introduction
- ✓ 2: Integrate-and-Fire (and generalisations)
- ➔ 3. Quality of Integrate-and-Fire models

Validation of neuron models



Real neuron vs. Nonlinear I&F Cortical layer V pyramidal neuron

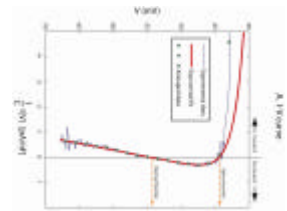
exponential Integrate-and-fire Model



$$t \cdot \frac{d}{dt}u = u - u_{rest} + \Delta \exp\left(\frac{u - J}{\Delta}\right) + R[I(t)]$$

$u(t) = \Theta \Rightarrow$ Fire --- reset of u

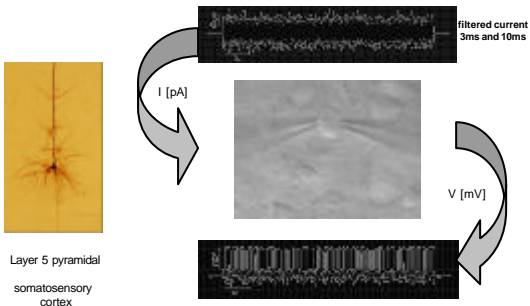
Measurement of the dynamic IV curve



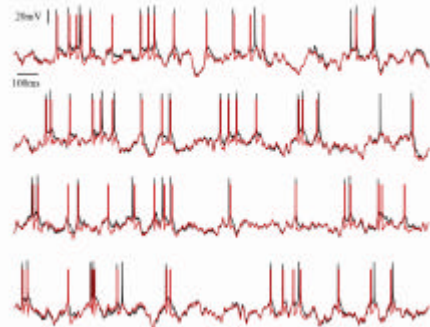
Experiments: Sandrine Lefort
Carl Petersen

Theory: Laurent Badel
Magnus Richardson

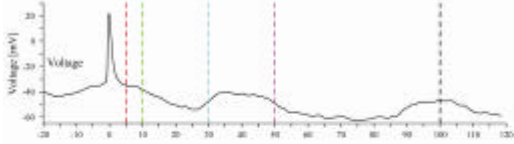
Experimental method



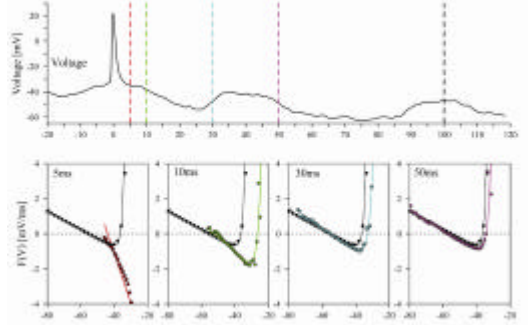
Comparison of the voltage traces



The after-spike neuronal response function

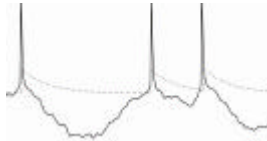


The post-spike neuronal response function



EIF with a dynamic threshold, resting potential and time constant

$$\frac{dV}{dt} = \frac{(E_L - V)}{t_L} + \frac{\Delta_T}{t_L} \exp\left(\frac{V - V_L}{\Delta_T}\right)$$



$$\frac{dV_L}{dt} = \frac{(V_{res} - V_L)}{t_{V_L}}$$

Fuortes and Mantegazzini (1962)

$$\frac{dE_L}{dt} = \frac{(E_{res} - E_L)}{t_E}$$

Jolivet et al (2003)
Rauch et al (2003)
Brette and Gerstner (2005)

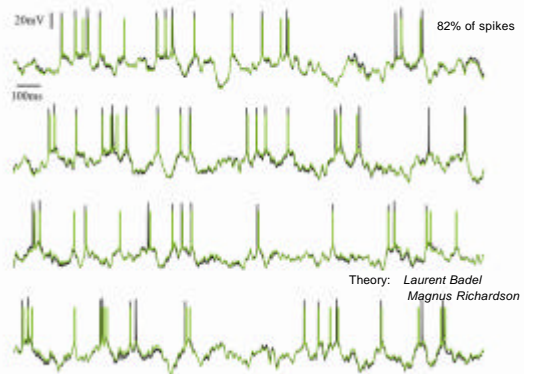
With a high reset:

$$V_{res} = -39mV > V_L = -41mV$$

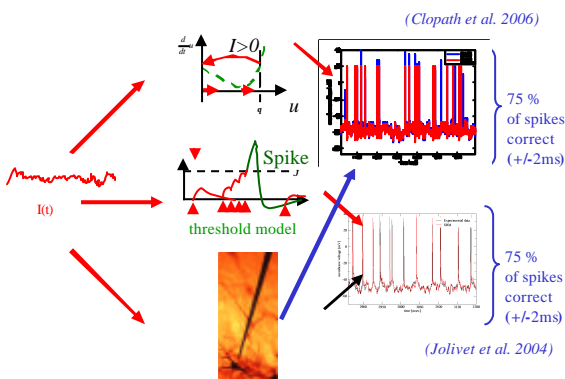
$$\frac{dt_L}{dt} = \frac{(t_{res} - t_L)}{t_{t_L}}$$

Wehmeier et al (1989)

Comparison of the model and experiment for the voltage trace



Validation of neuron models



Integrate & Fire:

Where is the firing threshold?

- ✓ 1: Introduction
- ✓ 2: Integrate-and-Fire (and generalisations)
- ✓ 3. Quality of Integrate-and-Fire models