Week 15 – transients and rate models



Biological Modeling of Neural Networks:

Week 15 – Fast Transients and **Rate models**

- Wulfram Gerstner
- EPFL, Lausanne, Switzerland



15.1 Review Populations of Neurons - Transients 15.2 Rate models

Week 15-part 1: Review: The brain is complex Neuronal Dynamics – Brain dynamics is complex

10 000 neurons 3 km of wire



motor cortex



frontal cortex

to motor output

Week 15-part 1: Review: Homogeneous Population



Homogeneous population: -each neuron receives input from k neurons in the population -each neuron receives the same (mean) external input (could come from other populations) -each neuron in the population has roughly the same parameters

Example: 2 populations



excitation

inhibition

Week 15-part 1: Review: microscopic vs. macroscopic



microscopic: -spikes are generated by individual neurons -spikes are transmitted from neuron to neuron

macroscopic: Population activity A_n(t) Populations interact via A_n(t)

Week 15-part 1: Review: coupled populations



Week 15-part 1: Example: coupled populations in barrel cortex

Neuronal Populations

= a homogeneous group of neurons (more or less)

Populations:

- pyramidal neurons in layer 5 of barrel D1
- pyramidal neurons in layer 2/3 of barrel D1
- inhibitory neurons in layer 2/3 of barrel D1

100-2000 neurons

per group (Lefort et al., NEURON, 2009)

different barrels and layers, different neuron types \rightarrow different populations





Fig. 15.3: Transient response of neurons in visual cortex. At t = 0 a high-contrast grating is flashed on a gray screen. Top left: A neuron in visual cortex V1 of a behaving monkey responds with a sharp onset after a latency of 27ms, as shown by the PSTH. Bottom left:

AWeek 15-part 2: A(t) in experiments: auditory click stimulus





Fig. 15.2: Response of auditory neurons across different layers to short stimuli. **A**. Left Schematic drawing of an electrode with 32 sites overlayed on top of stained cortical tissues in order to show that the electrode crosses all cortical layers. Right: Spike responses o

Experimental data: Sakata and Harris, 2009

T 2/3	
L2/J	
Τ Λ	
L4	
ł	
<u> </u>	
T	
16	•
LO	
I	
_	



Week 15-part 1: *A(t)* in simulations of integrate-and-fire neurons Simulation data: Brunel et al. 2011 Α 80-80- $\tau_{s} = 10 \text{ ms}$ A(t) [Hz] A(t) [Hz] $\tau_s = 0 \text{ ms}$ **60** 60 40 Image: 40 20 20 Neuronal Dynamics, I(t)I(t)2014

10 ms

Fig. 15.9: Slow (colored) diffusive noise versus white diffusive noise. A population of integrate-and-fire models with a time constant of $\tau_m = 20$ ms was simulated and responses to a step stimulus reported in time bins of 1ms. A. Colored noise with a filtering time constant $\tau_s = 10$ ms leads to an abrupt, instantaneous response. **B**. White noise leads to a smoothly increasing fairly slow response. Figures adapted from (Brunel et al., 2001).



10 ms

Week 15-part 1: *A(t)* in simulations of integrate-and-fire neurons



Fig. 15.1: Transients and rate models. All neurons receive the same step current stimulus at time $t_{\rm ON} = 100$ ms. A randomly connected network of 8000 excitatory and 2000

Week 15 – transients and rate models



Biological Modeling of Neural Networks:

Week 15 – Fast Transients and **Rate models**

Wulfram Gerstner

EPFL, Lausanne, Switzerland



Conclusion of part 1

Transients are very fast -In experiments -In simulations of spiking neurons

Week 15-part 2: Rate model with differential equation

A(t) = g(h(t)) $\tau \frac{d}{dt} h(t) = -h(t) + R \cdot I(t)$ $h(t) = \int_0^\infty \varepsilon s I(t-s)ds$ Input potential I(t)*h(t)*

Differential equation can be integrated!, exponential kernel

Week 15-part 2: Rate model: step current



Example LNP rate model: Linear-Nonlinear-Poisson Spikes are generated by a Poisson process, from rate model

Week 15-part 2: *Wilson-Cowan model*: step current





Week 15-part 2: Aim: from single neuron to population

Single neurons

- model exists
- parameters extract
- works well for step
- works well for time



rom data rent current

Population of Neurons? Population equation for A(t)-existing models - integral equation





Week 15-part 2: *A(t)* in simulations : step current

25000 identical model neurons (GLM/SRM with escape noise) parameters extracted from experimental data



simulation data: Naud and Gerstner, 2012

Week 15-part 2: rate model



Simple rate model:

- too slow during the transient - no adaptation

Week 15-part : rate model with adaptation



Week 15-part 2: rate model

Simple rate model: - too slow during the transient - no adaptation

Adaptive rate model:

- too slow during the transient
- final adaptation phase correct

Rate models can get the slow dynamics and stationary state correct, but are wrong during transient





Week 15-part 2: improved rate models/population models

Improved rate models a) rate model with effective time constant → next slides b) integral equation approach → chapter 14

Week 15-part 2: *Rate model* with effective time constant

A(t) = F(h(t))

 $\tau_{eff}(t)\frac{d}{dt}h(t) = -h(t) + R \cdot I(t)$

$\rightarrow \qquad \text{Input potential} \\ I(t) \qquad f(t) \qquad h(t) \qquad h(t) \qquad f(t) \ f(t$

Shorter effective time constant during high activity

 $\tau_{eff}(t) \sim F' / A_0(t)$

+ $R \cdot I(t)$ Ostojic-Brunel, 2011

 $h(t) = \int_0^\infty \varepsilon \ s \ I(t-s)ds$

Week 15-part 2: Rate model with effective time constant

A(t) = F(h(t))

 $\tau_{eff}(t)\frac{d}{dt}h(t) = -h(t) + l \operatorname{E}_{\mathrm{V}}^{100}$ Ostojic-Brunel, 2011

 $\tau_{eff}(t) \sim F' / A_0(t)$

→Shorter effective time constant during high activity→Theory fits simulation very well

I [a.u.]



Week 15-part 2; Conclusions

Rate models

- are useful, because they are simple
- slow dynamics and stationary state correct
- simple rate models have wrong transients
- improved rate models/population activity models exist

re simple ary state correct rong transients ulation activity models exist

The end

Reading: Chapter 15 of NEURONAL DYNAMICS, Gerstner et al., Cambridge Univ. Press (2014)