

Introduction to Computational Neuroscience

Neural Coding

Martin Nawrot

Oct 12, 2011

Time table

	Mon 10 Oct.	Tue 11 Oct	Wed 12 Oct	Thu 13 Oct.	Fri 14 Oct
Course Organizer		M. Voelkle	M. Nawrot	M. Nawrot / S. Schreiber	S. Kiebel / M. Nawrot
9.15– 10.45	no lectures	The General Linear Model I (Correlation and Regression Analysis) <ul style="list-style-type: none"> - Correlation Analysis - Hypothesis Testing - Effect Sizes - Power Chapter 2, 3, 4.3., 4.4	<i>Lecture</i> Introduction to Computational Neuroscience 1: Data, Analyses, Modeling.	<i>Lecture</i> Modelling single neurons: The Hodgkin-Huxley Model	
Break					
11.00– 12.30	no lectures	The General Linear Model II (Regression Analysis "vs." ANOVA) <ul style="list-style-type: none"> - Multiple Regression - ANOVA - Dummy / Effects Coding - Hierarchical F-Test Chapter 4,8	<i>Lecture</i> Introduction to Computational Neuroscience 2: Neural Coding	<i>Exercises (Matlab)</i> Hodkin-Huxley Model	Lecture Cognitive Neuroscience I
Break					
13.30– 15.00	no lectures	Path Analysis and "Causal" Models <ul style="list-style-type: none"> - Path Analysis and Path Coefficients - Direct, Indirect, Total, Zero-Order, & Spurious Effects Chapter 12	<i>Exercises (Matlab)</i> Rate Coding, Tuning Curves	<i>Lecture</i> Probabilistic modelling of spike trains: Point process theory and application (neural variability)	<i>Lecture</i> <i>Cognitive Neuroscience II</i>
Break					After last session: Multiple Choice Test, 30 questions
15.15– 16.45	no lectures	Advanced Methods (Structural Equation Models and Multilevel Models) <ul style="list-style-type: none"> - Structural Equation Models - Hierarchical Linear Models Chapter 12, 14	<i>Exercises (Matlab)</i> Bayesian decoding of movement parameters from neural spike trains.	<i>Exercises (Matlab)</i> Simulation of point processes / Variability of spike trains	

Exercises: Computer Pool, Room 224

Our Team



Biology | Biophysics | Bioinformatics | Computational Biology
Computational Neuroscience | Computer Science | Econometrics
Engineering | Information Technology | Physics | Mathematics

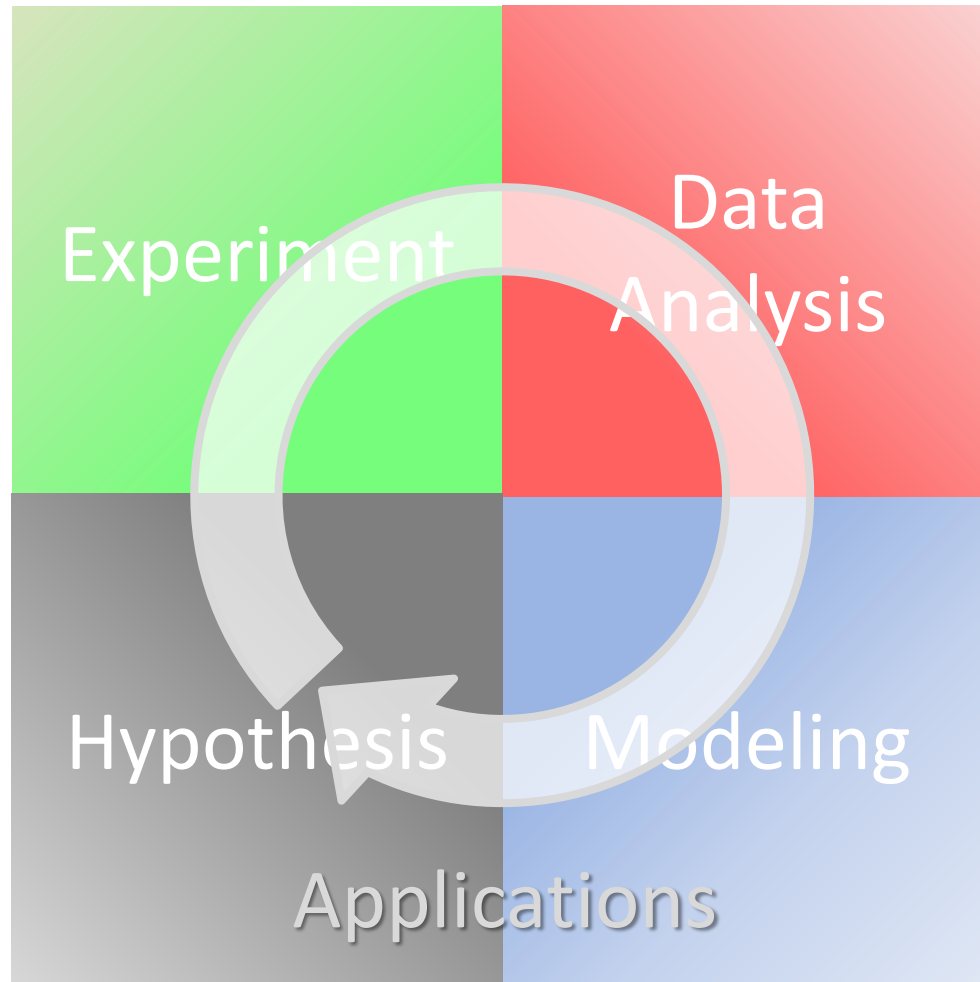
Outline

Introduction

Spatial and Temporal Scales of Brain Signals

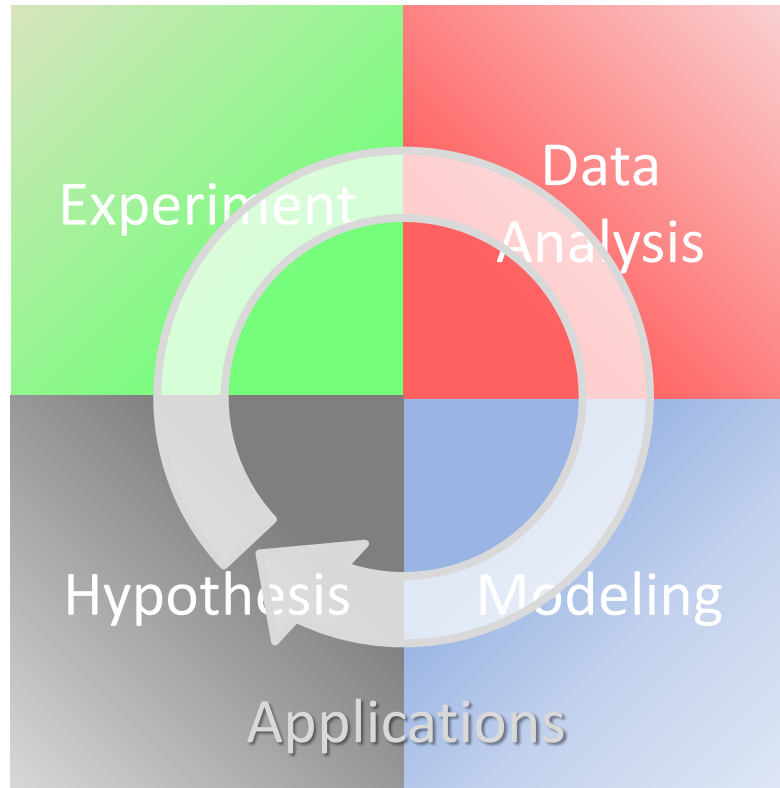
Neural Coding

Introduction



Electrophysiology
Imaging Data
Behavioral Experiments
(Insects and Primates)
Cortical Slice Recordings

Experimental Design
Model Design
Grant Proposals



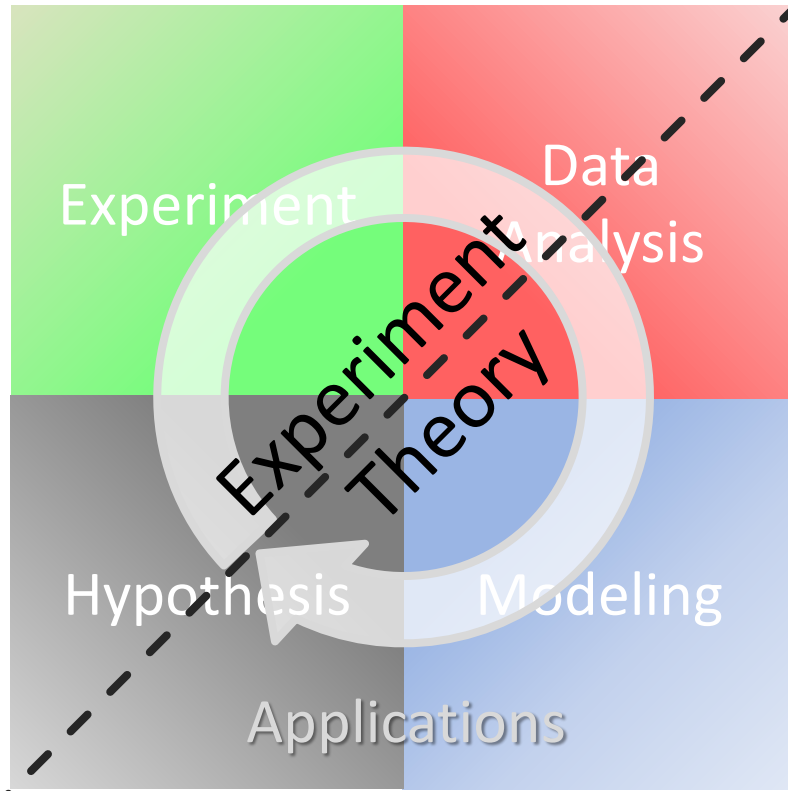
Statistics of Animal Behavior
Spike Train Statistics
Machine Learning
Linear Systems Analysis
Dynamical Systems Analysis
GLM

Point Process Theory
Dynamical System Theory
Machine Learning
Spiking Neural Networks

Neuromorphic Hardware
Neuromorphic Robots

Electrophysiology
Imaging Data
Behavioral Experiments
(Insects and Primates)
Cortical Slice Recordings

Experimental Design
Model Design
Grant Proposals



Statistics of Animal Behavior
Spike Train Statistics
Machine Learning
Linear Systems Analysis
Dynamical Systems Analysis
GLM

Point Process Theory
Dynamical System Theory
Machine Learning
Spiking Neural Networks

Neuromorphic Hardware
Neuromorphic Robots

Models in computational neuroscience ...

phenomenological model

functional model

biophysical model

abstract model

statistical model

mechanistic model

mathematical model

Artificial Neural Network

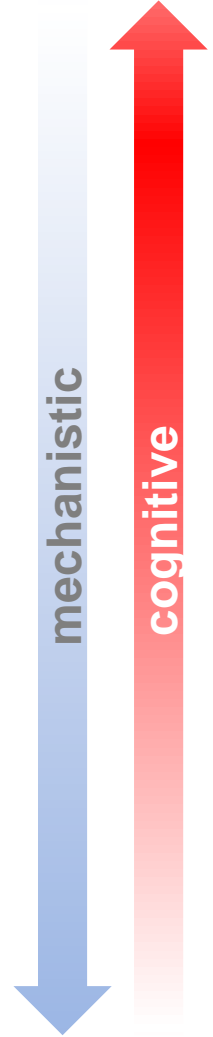
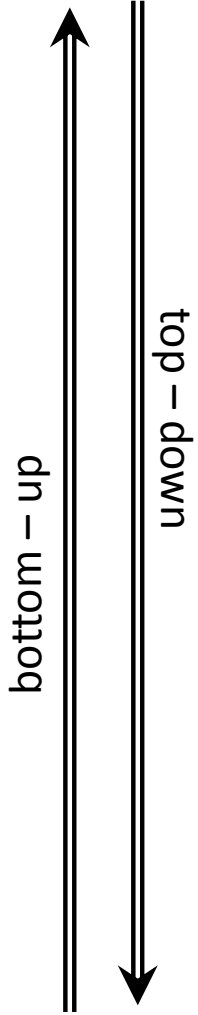
stochastic model

computational model

connectionist model

neural network model

BEHAVIOR and COGNITION

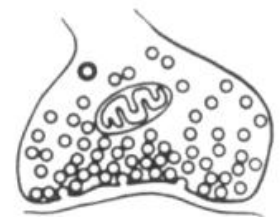
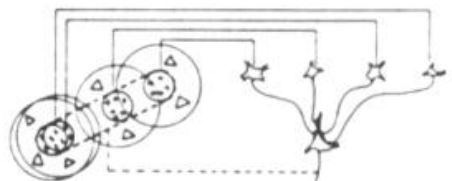
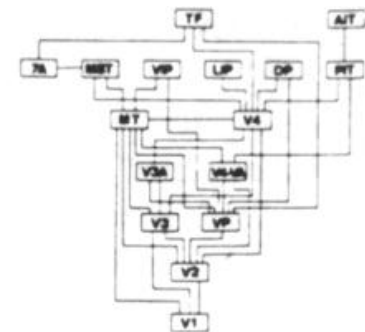
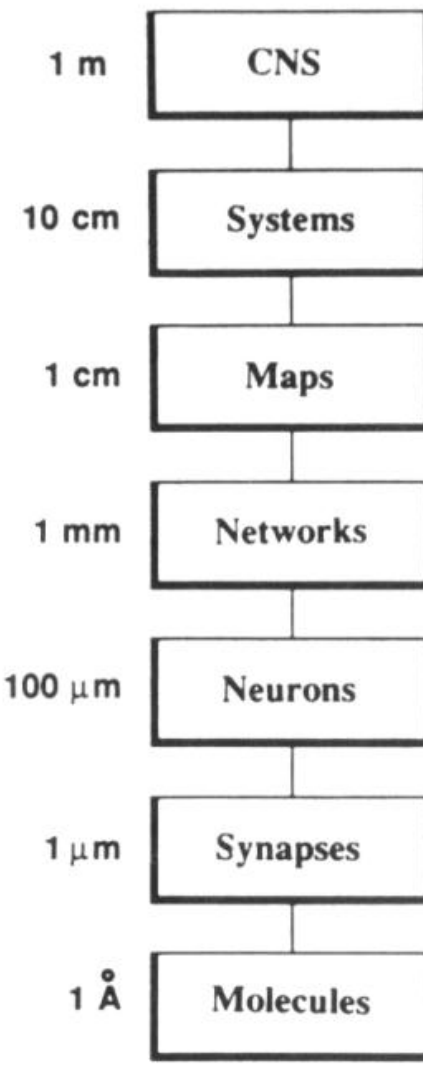
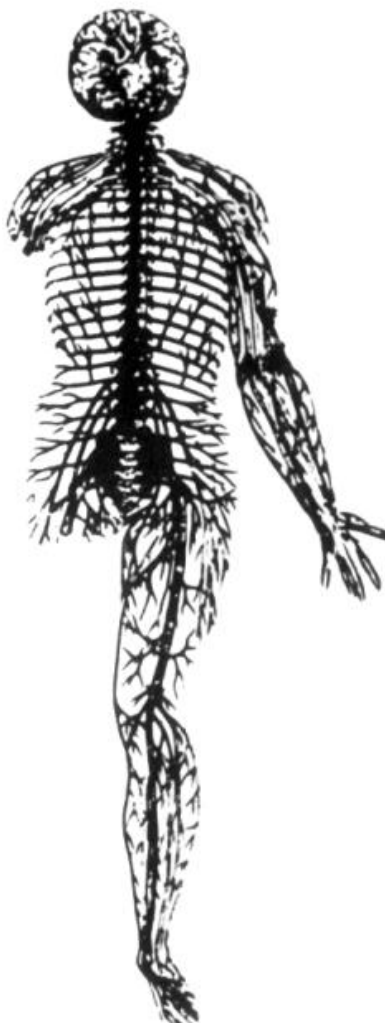


MOLECULES

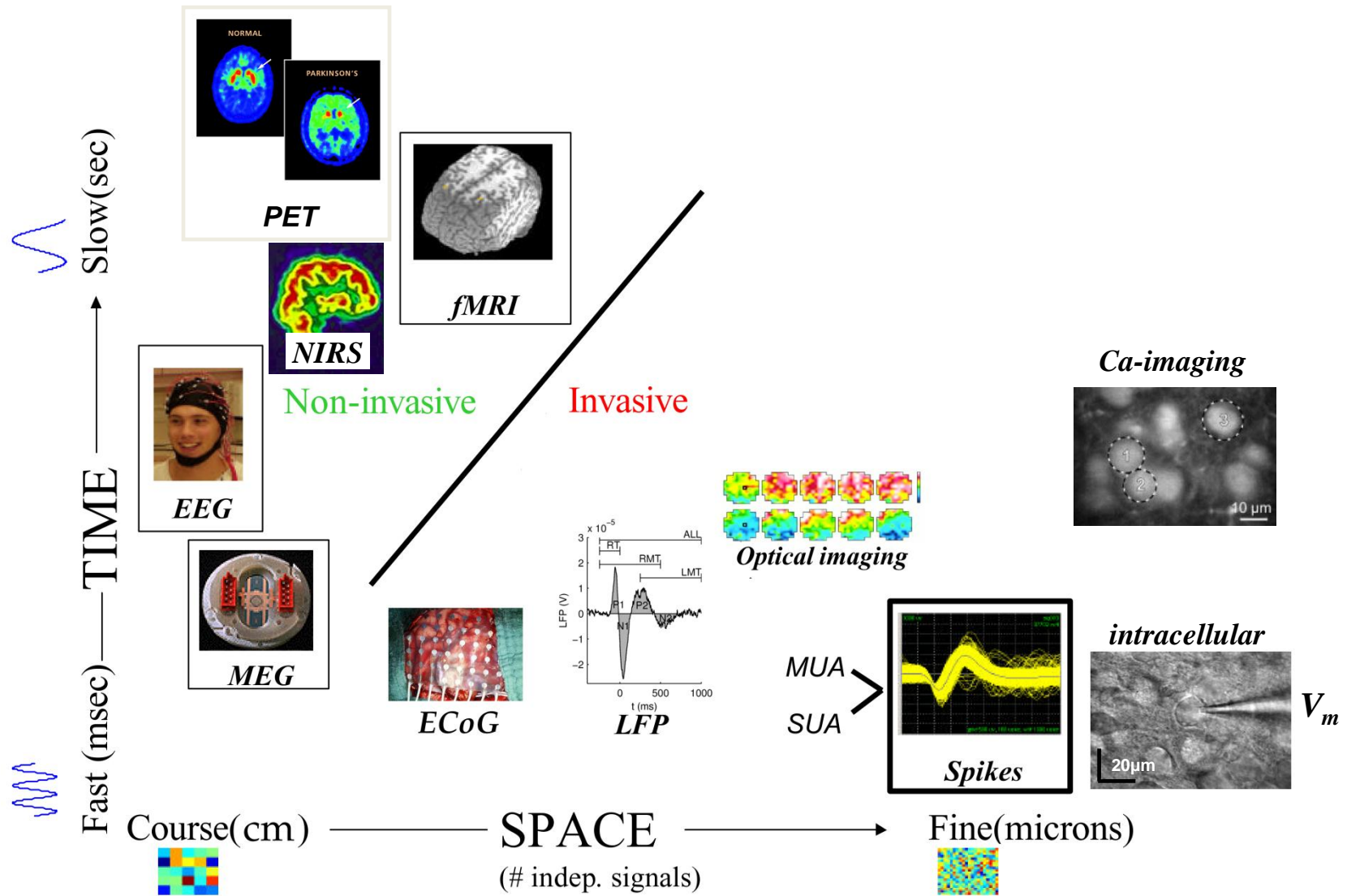
Spatial and Temporal Scales of Brain Signals

- Measurement techniques
- Neural output: spike train recordings

Spatial Scales

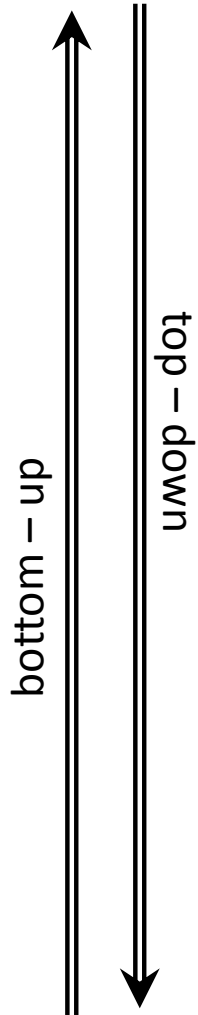


Resolution in Space and Time



(adapted from Matt Fellows)

BEHAVIOR and COGNITION



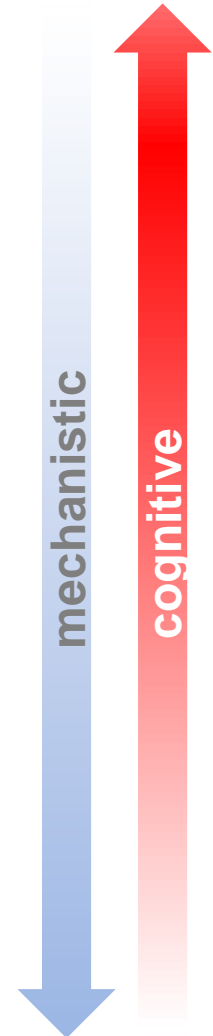
behavioral
(psychophysics, language, ...)

EEG / MEG
fMRI
PET
NIRS

local field potentials
multi-unit-activity

spike train recordings
intracellular measurements
Ca imaging

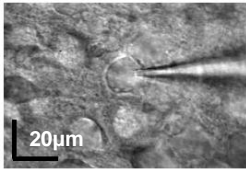
MOLECULES



Direct vs. Indirect Measures of Neuronal Signals

electrophysiology

■ direct measurement of neuronal signals

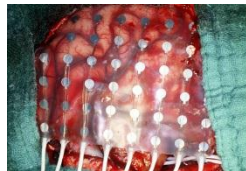


intracellular recording from
- single neurons / dendrites



extracellular recording of
- action potentials (SUA/MUA) *and*
- local field potential (LFP, indirect)

■ measurement of electric mass signals



electrocorticography (ECoG)
- epicortical field potentials



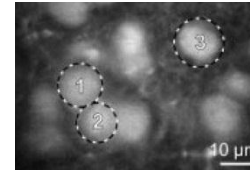
electroencephalography (EEG)



magnetoencephalography (MEG)

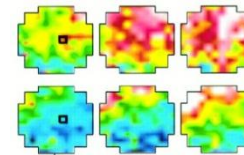
imaging

■ visualization of single neuron activity

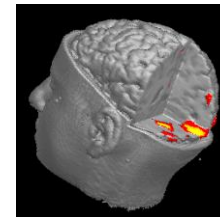


optical imaging of
intracellular Ca activity
- *in vitro* / *in vivo*
- 2D / 3D

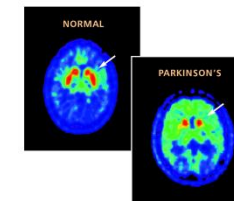
■ visualization of average activity



optical imaging with
voltage sensitive dyes



functional magnetic
resonance imaging (fMRI)



positron emission tomography (PET)

Intracellular recording

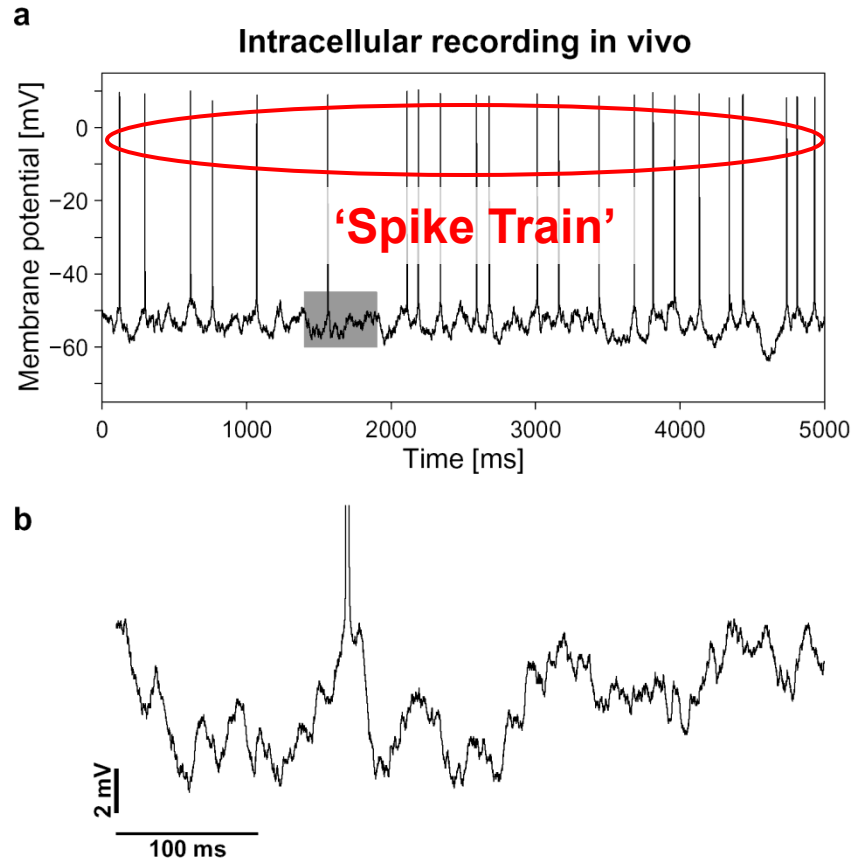
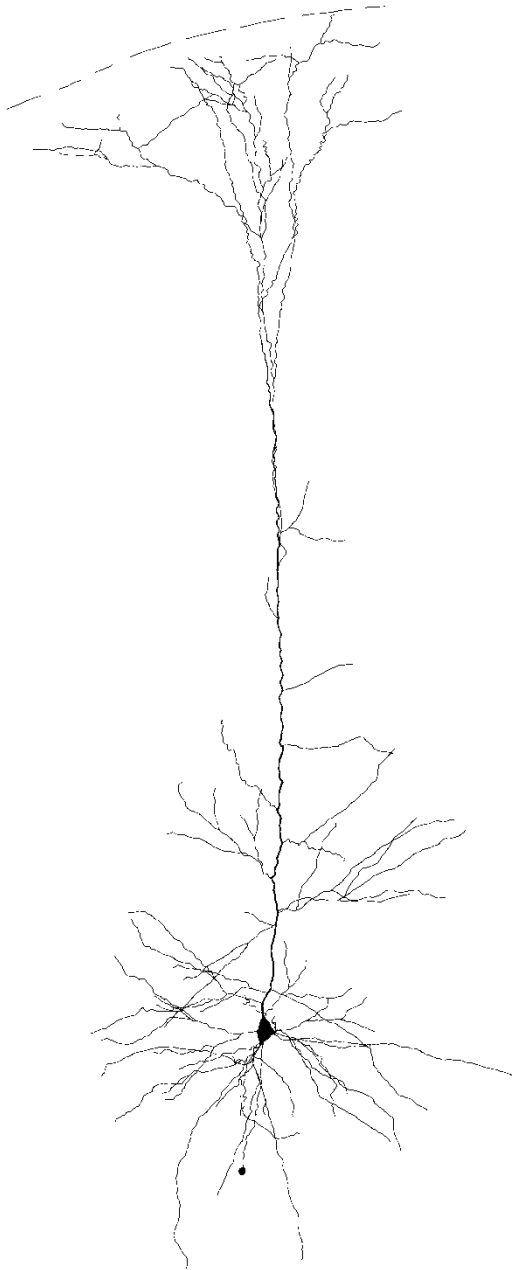
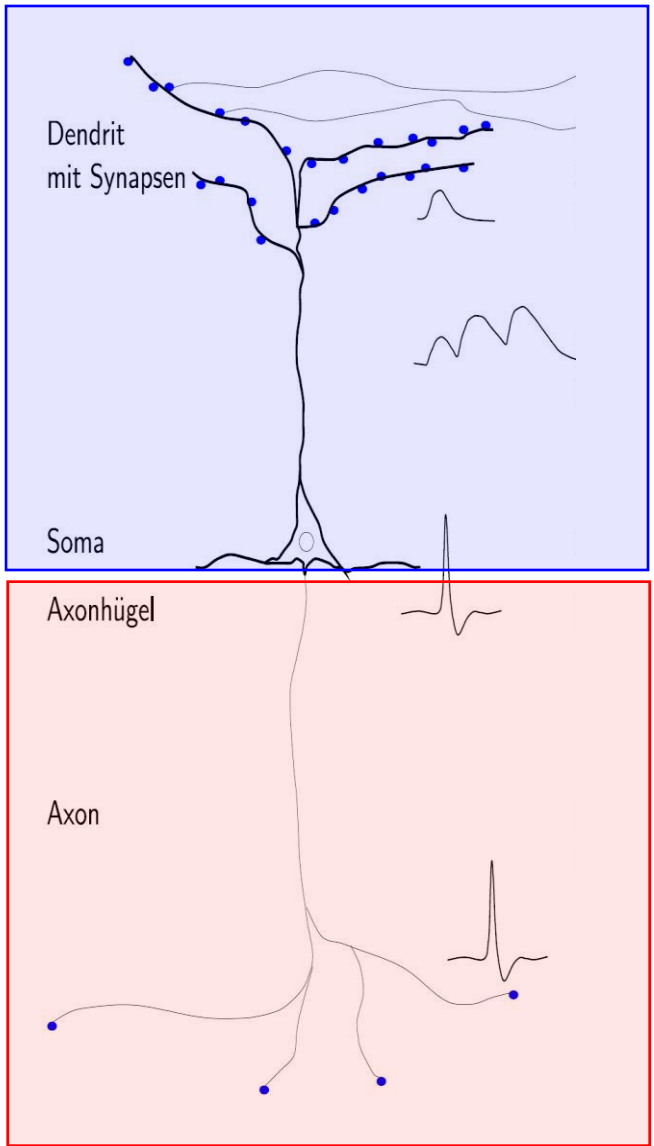


Figure 1. Permanent background input *in vivo* causes dynamic fluctuations of the membrane potential and drives the neuron to spontaneous spiking activity. (A) Membrane potential recorded intracellularly in the frontal cortex of the anesthetized rat. Presynaptic inputs from several hundreds or thousand of presynaptic neurons cause depolarization of the cell to a resting potential of about -50 mV and salient fluctuations of the membrane potential. (B) The enlarged cut-out from A reveals the fine structure of the signal that results from the superposition of many single EPSPs and IPSPs and gives an impression of the time scale on which these fluctuations take place. Data by courtesy of Detlef Heck (Léger, Stern, Aertsen, & Heck, 2003).

Extracellular recording

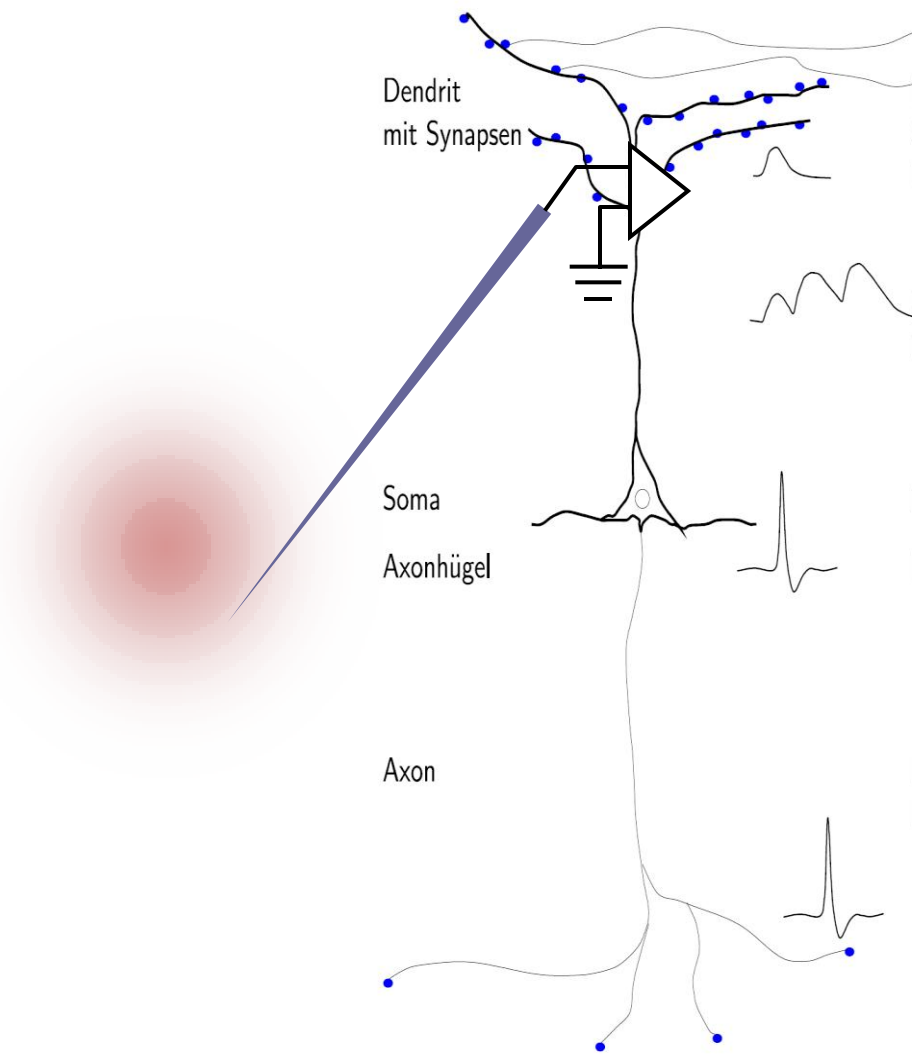
© Clemens Boucsein, Universität Freiburg



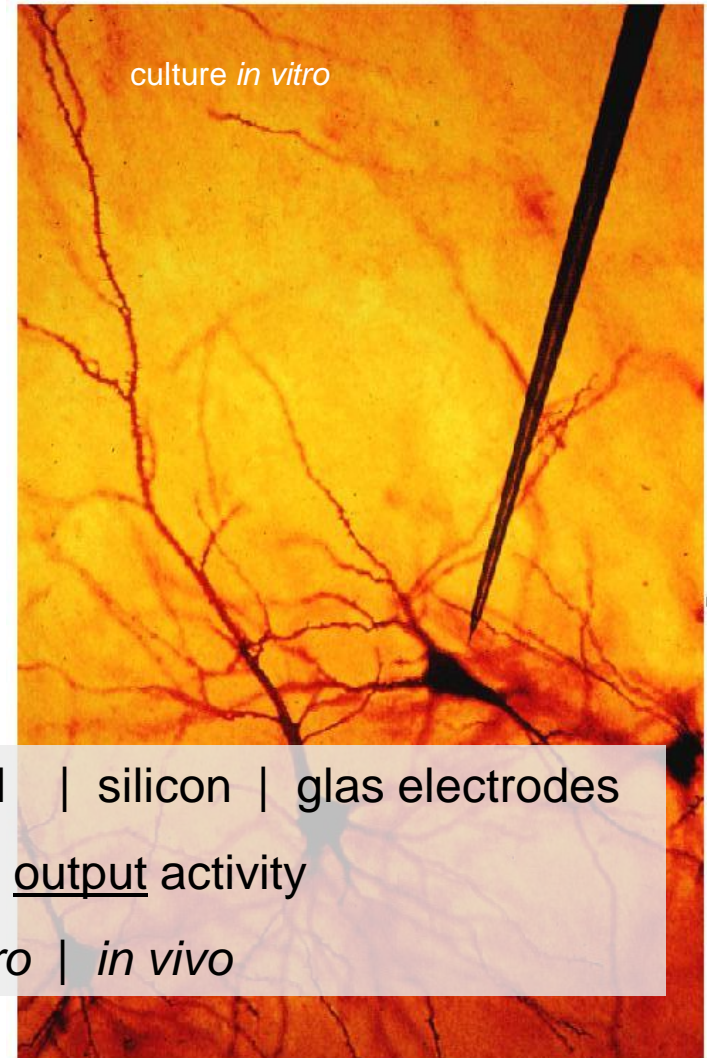
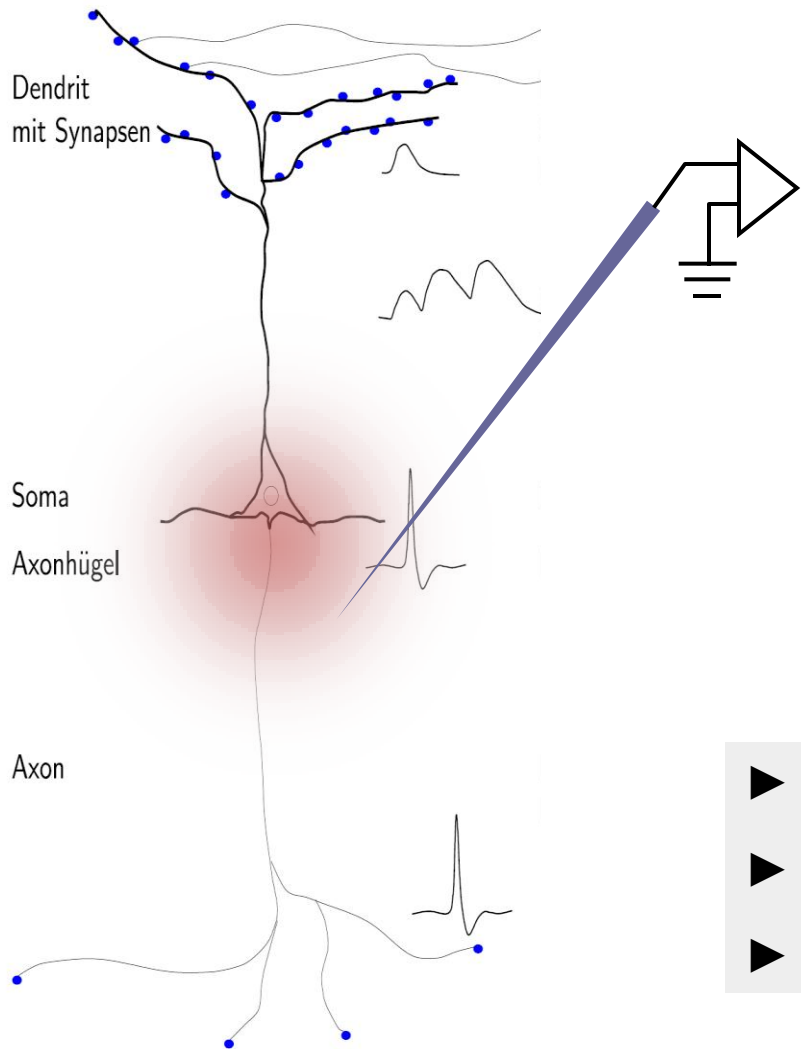
INPUT

OUTPUT

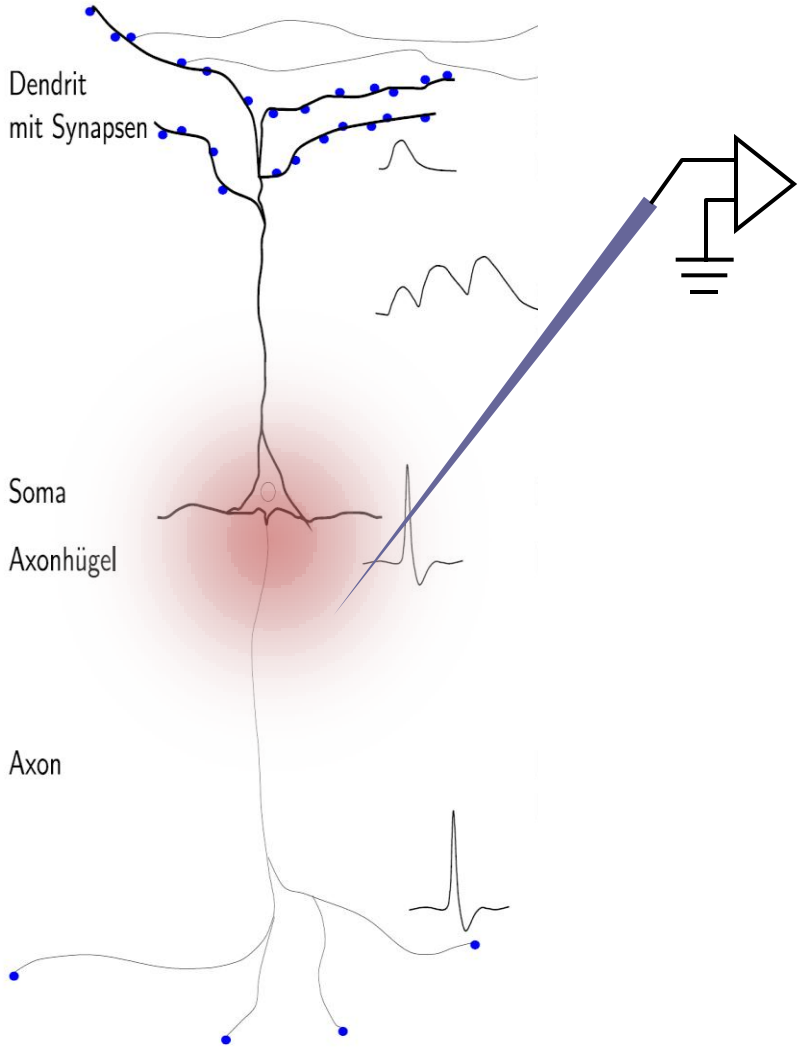
Extracellular recording



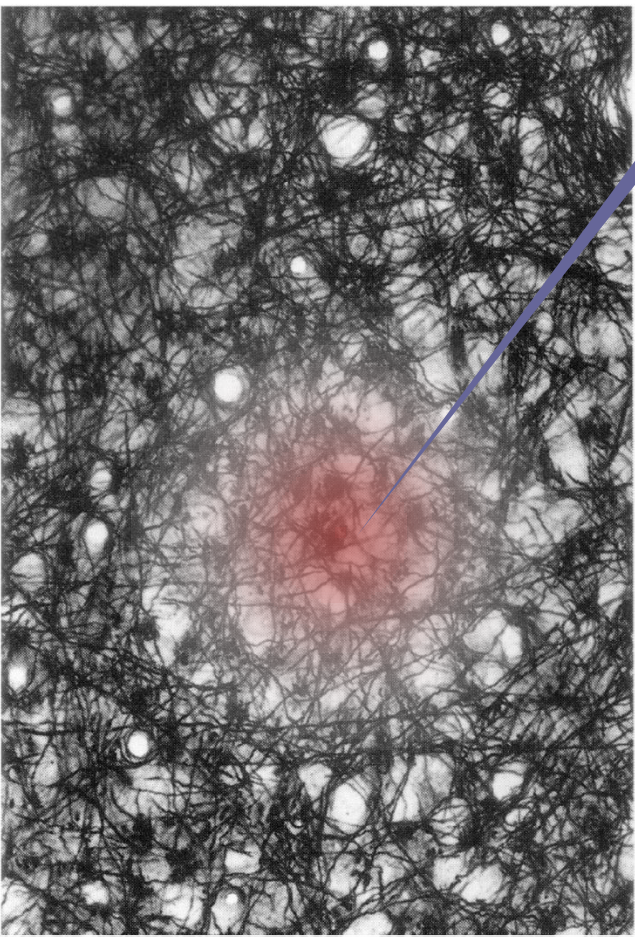
Extracellular recording



Extracellular recording



Cortex



Valentino Braitenberg & Almut Schüz
Cortex: Statistics and Geometry of Neuronal Connectivity
Springer, Berlin, 1998 (Second Edition)

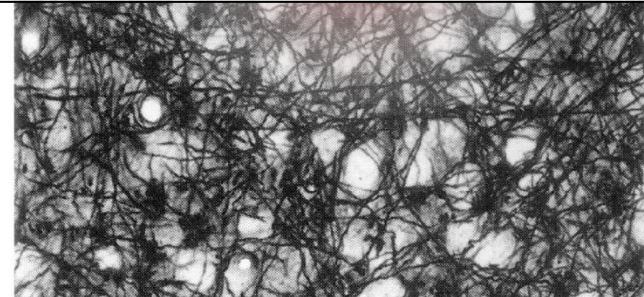
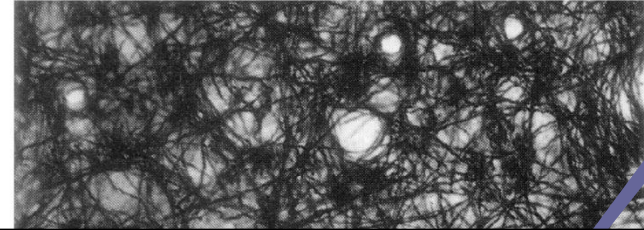
Extracellular recording

The Mouse Cortex

Total volume	$2 \times 87 \text{ mm}^3$
Total number of neurons	16 000 000
Number of sensory input fibres	$< 1\,000\,000$
Length of axonal tree	10–40 mm
Length of dendritic tree	4 mm
Range of axons	1/0.2 mm
Range of dendrites	1/0.2 mm
Density of neurons	$90\,000 / \text{mm}^3$
Density of axons	$4 \text{ km} / \text{mm}^3$
Density of dendrites	$0.4 \text{ km} / \text{mm}^3$
Density of synapses	$700\,000\,000 / \text{mm}^3$
Synapses per neuron	8 000
Probability of synaptic contact	0.1
Relative density of axons	$10^{-5} / 10^{-3}$
Relative density of dendrites	10^{-3}

Undersampling !

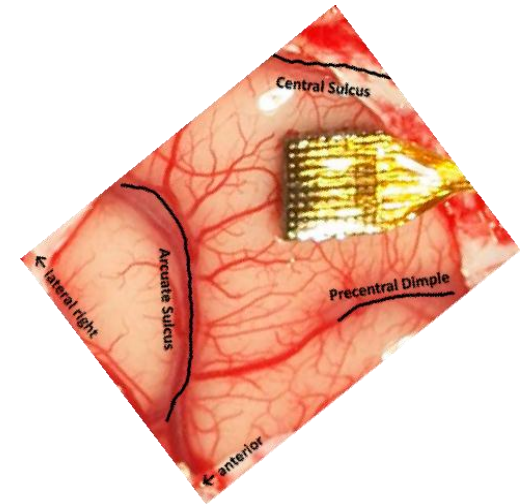
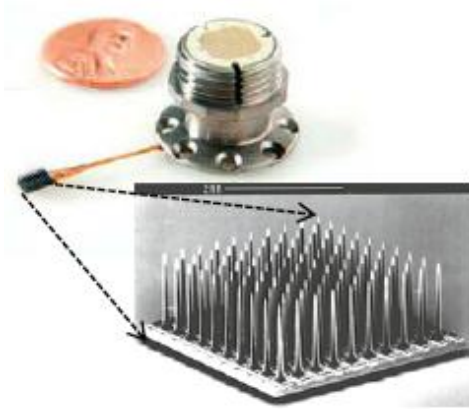
Cortex



Valentino Braitenberg & Almut Schüz
 Cortex: Statistics and Geometry of Neuronal Connectivity
 Springer, Berlin, 1998 (Second Edition)

field potential *spikes*

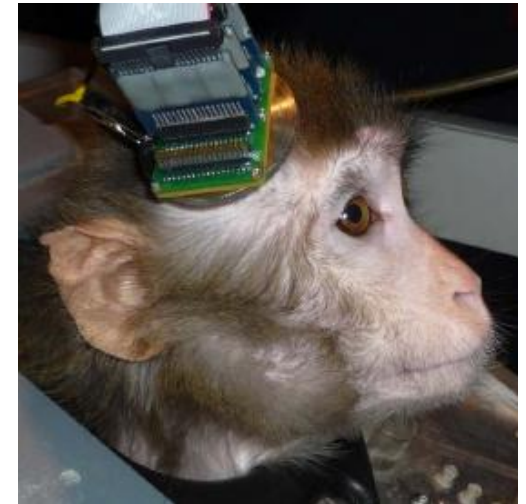
State of the art : 100 channels in parallel (Utah Array)



Positioning the array



Pneumatic insertion

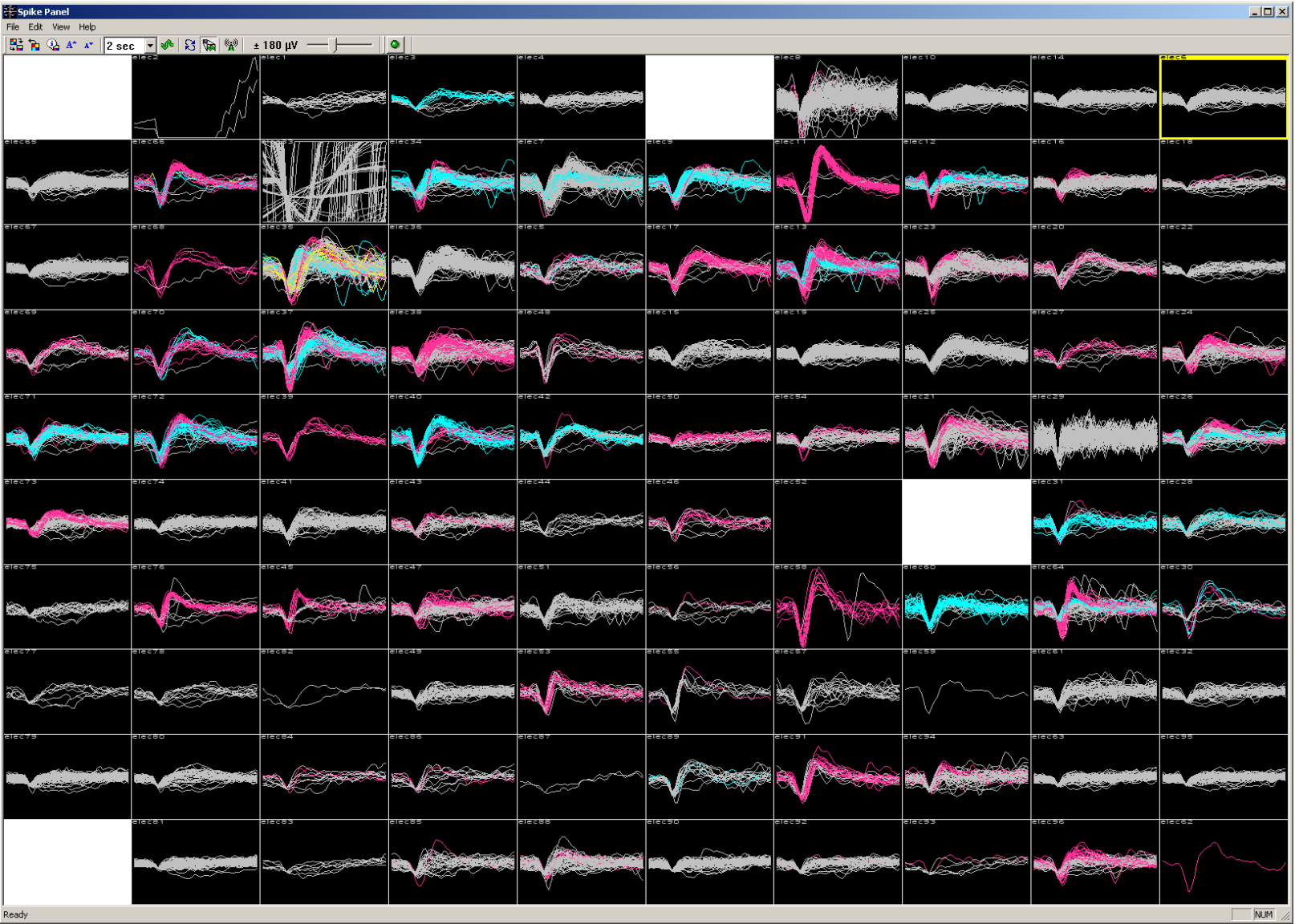


recordings

Thomas Brochier, Alexa Riehle, CNRS, Marseille.

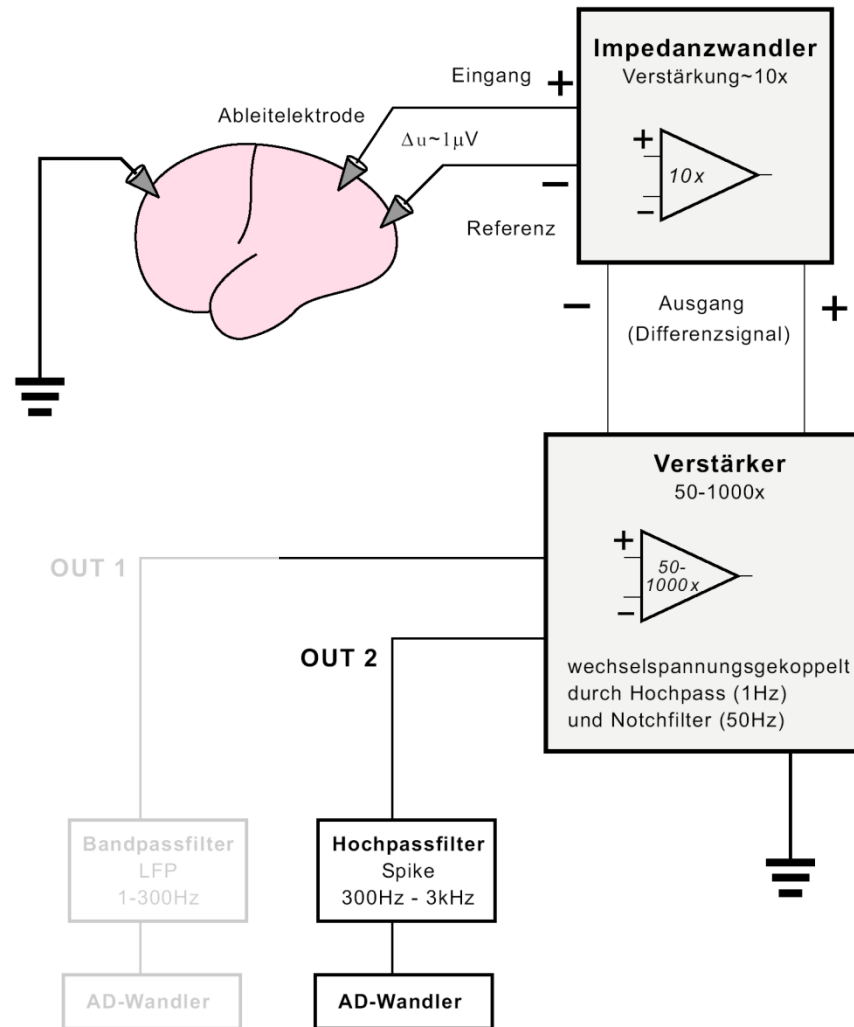
State of the art : 100 channels in parallel (Utah Array)

Monkey L
RH

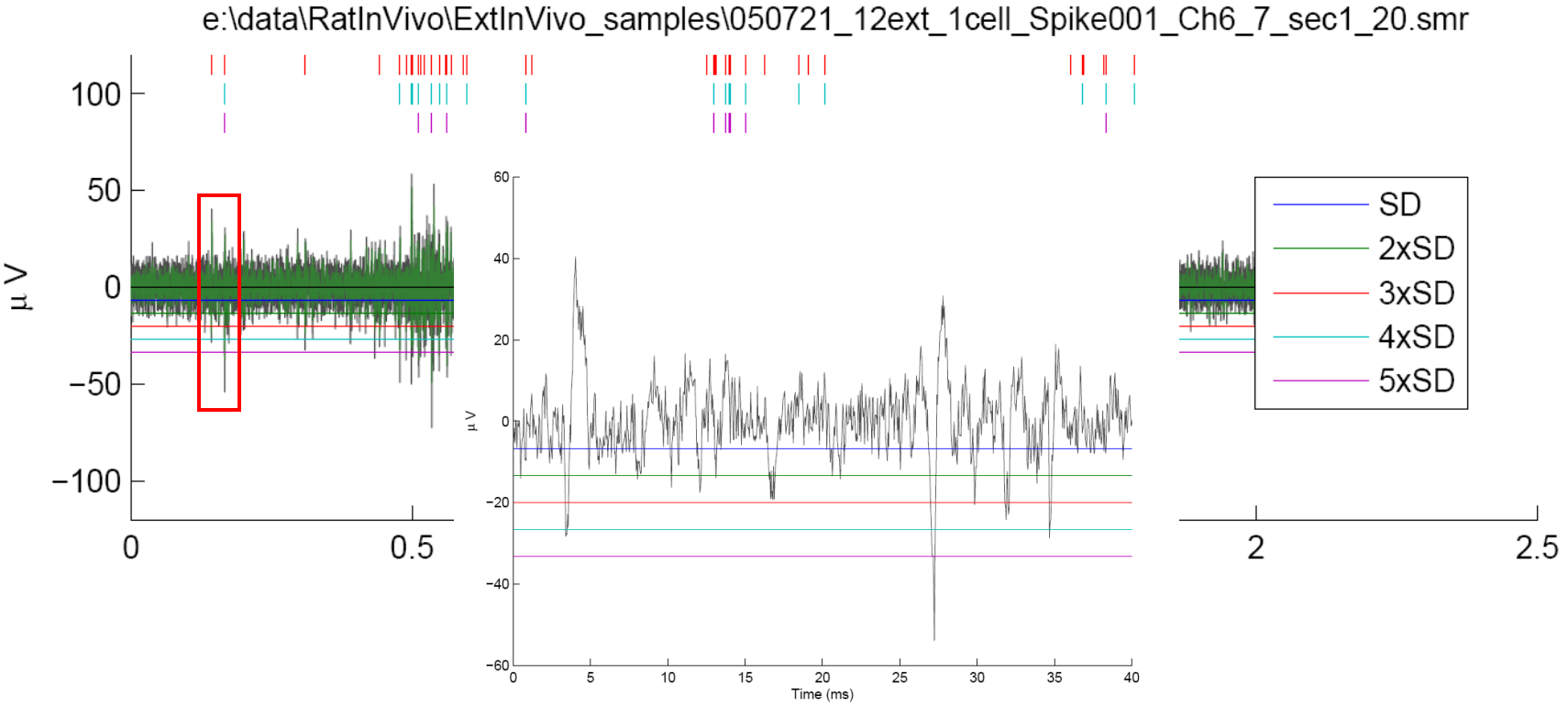


Thomas Brochier, Alexa Riehle, CNRS, Marseille.

Extracellular recording

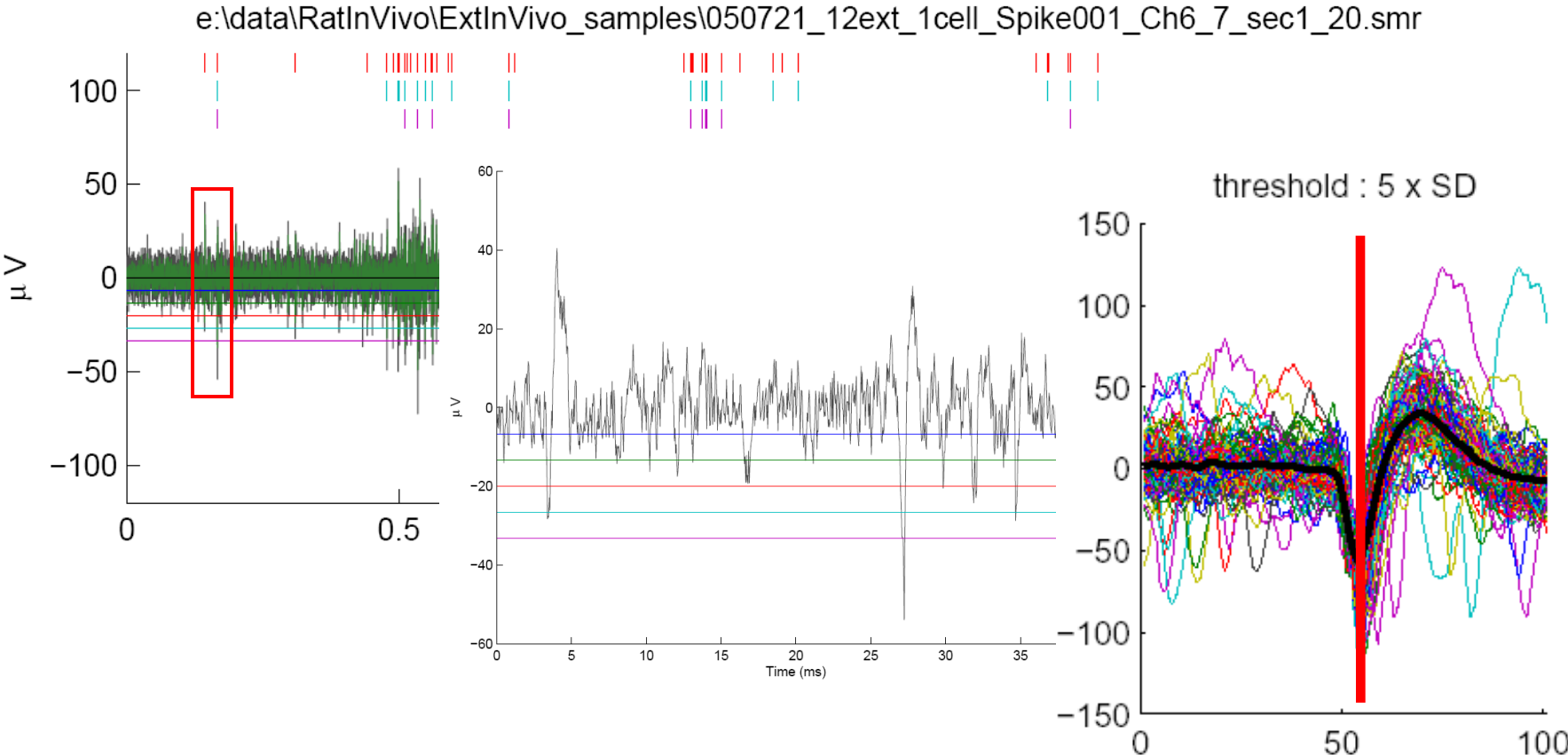


Extracellular recording: spikes



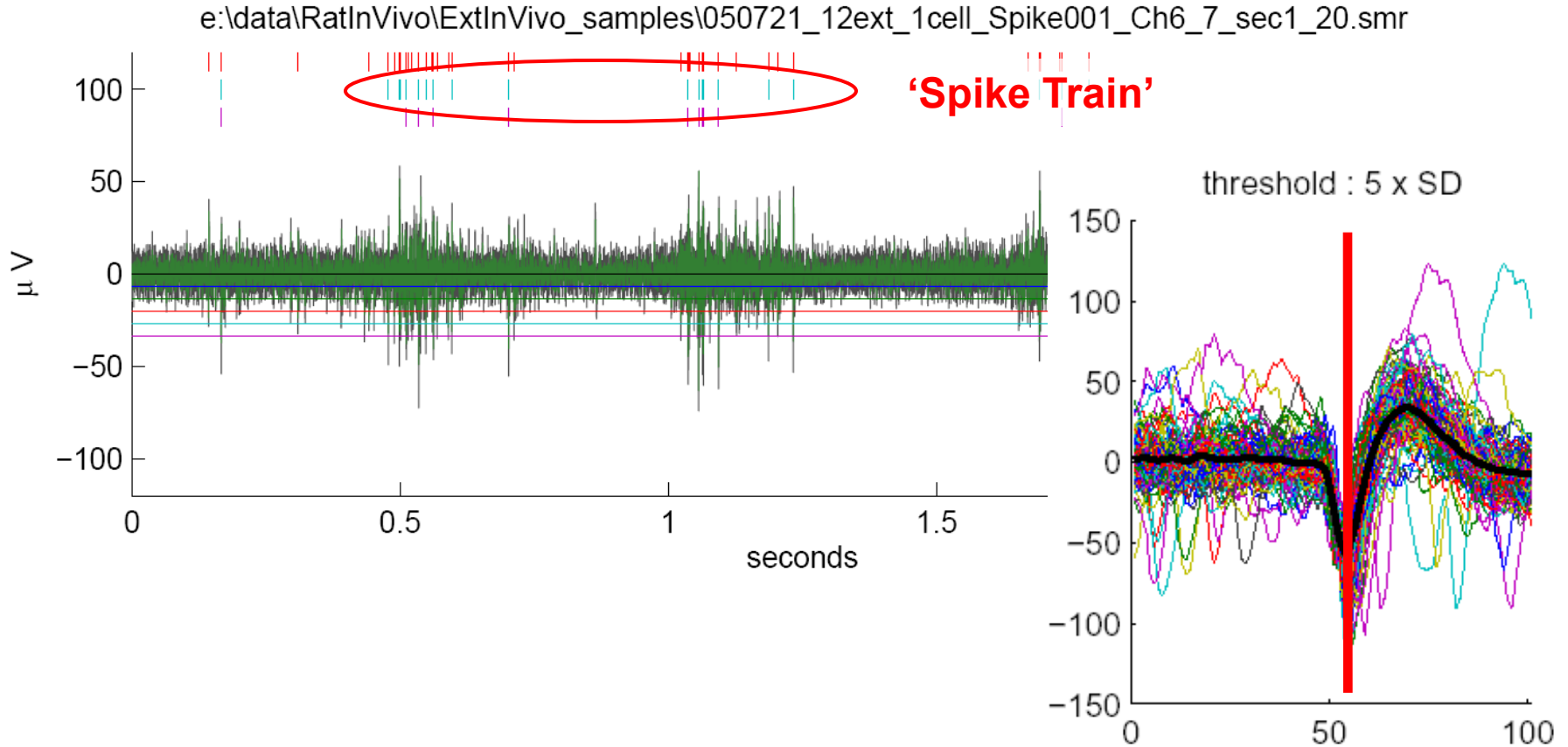
Extrazelluläre Aufnahmen im somatosensorischen Kortex der Ratte. Spontanaktivität unter Anästhesie.
Data Curtsey: Clemens Boucsein und Dymphie Suchanek, Neurobiologie & Biophysik, Universität Freiburg

Extracellular recording: spikes



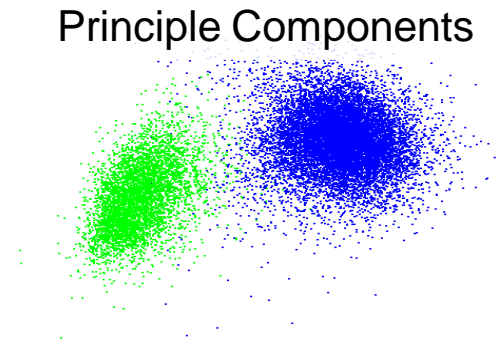
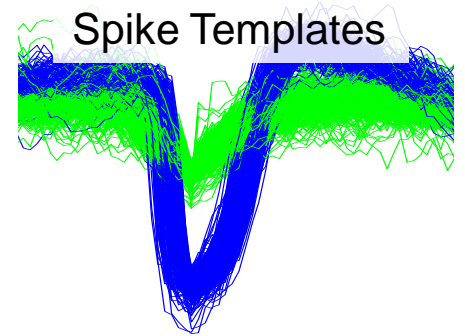
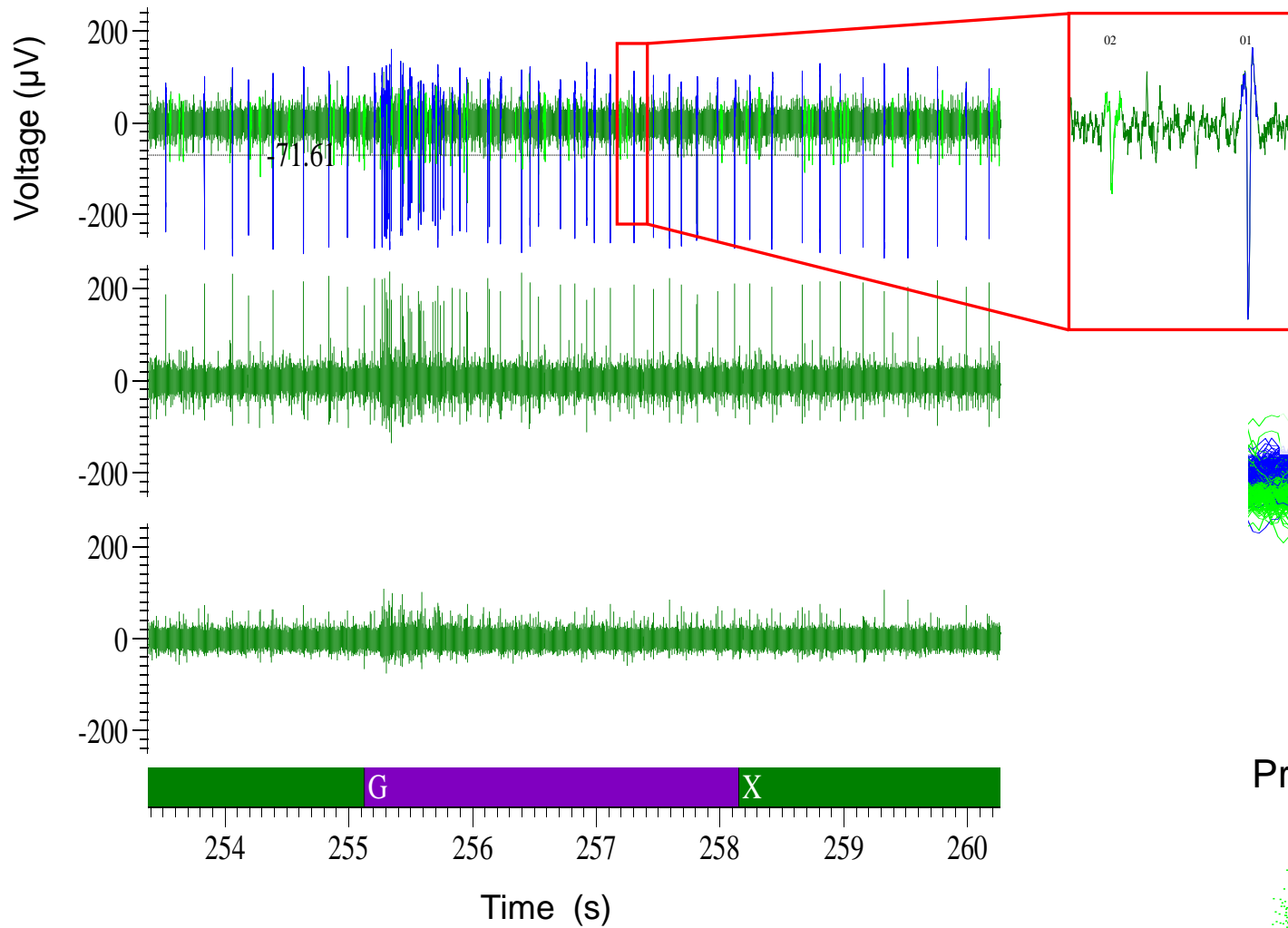
Extrazelluläre Aufnahmen im somatosensorischen Kortex der Ratte. Spontanaktivität unter Anästhesie.
Data Curtsey: Clemens Boucsein und Dymphie Suchanek, Neurobiologie & Biophysik, Universität Freiburg

Extracellular recording: spike train



Extrazelluläre Aufnahmen im somatosensorischen Kortex der Ratte. Spontanaktivität unter Anästhesie.
Data Curtsey: Clemens Boucsein und Dymphie Suchanek, Neurobiologie & Biophysik, Universität Freiburg

Extracellular recording: spike sorting



Extrazelluläre Aufnahmen von α -extrinsischen Neuronen im Bienenhirn. Antwort auf Duftreiz.
Data Curtsey: Dr. Martin Strube, Neurobiologie, Freie Universität Berlin

Extracellular recording: spike sorting

Estimated number of spike sorting errors :

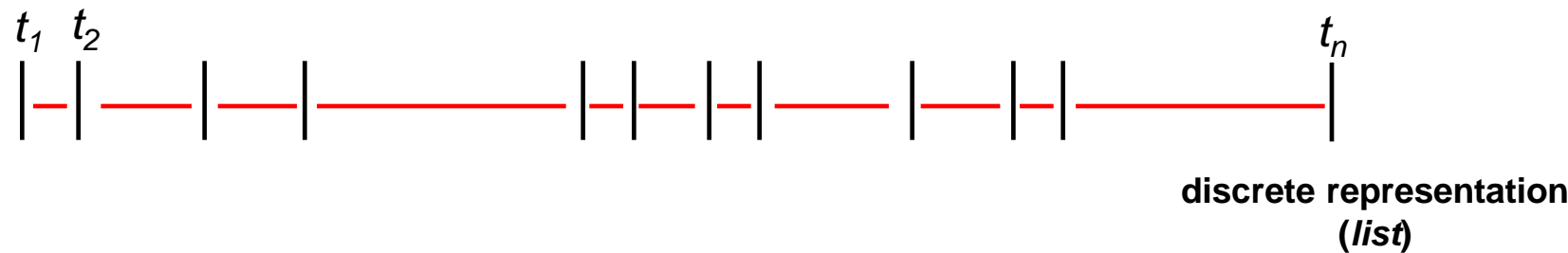
	[1]	[2]
false positive rate :	13%	~10%
false negative rate:	9%	~10%

single *unit* activity \neq single *neuron* activity

[1] Joshua, Elias, Levine, Bergman (2007) *J Neurosci Meth* doi: [jneumeth.2007.03.012](https://doi.org/10.1016/j.jneumeth.2007.03.012)

[2] Pouzat, Delescluse, Viot, Diebolt (2004) *J Neurophysiol* 91

Neural output: spike train



10100001000100000000001010010100000100010100000000001

binary representation
(*array*)

‘ spike train ‘

discrete time series of events

Neural Coding I

- Rate Code vs. Temporal Code

Rate Code vs. Temporal Code

Rate Code

- concept: information encoded in neuronal **firing rate**
- **population code** permits encoding of precise information
- **redundancy** in large populations permits fast transmission
- neuron acts as '***Integrator***'

Temporal Code

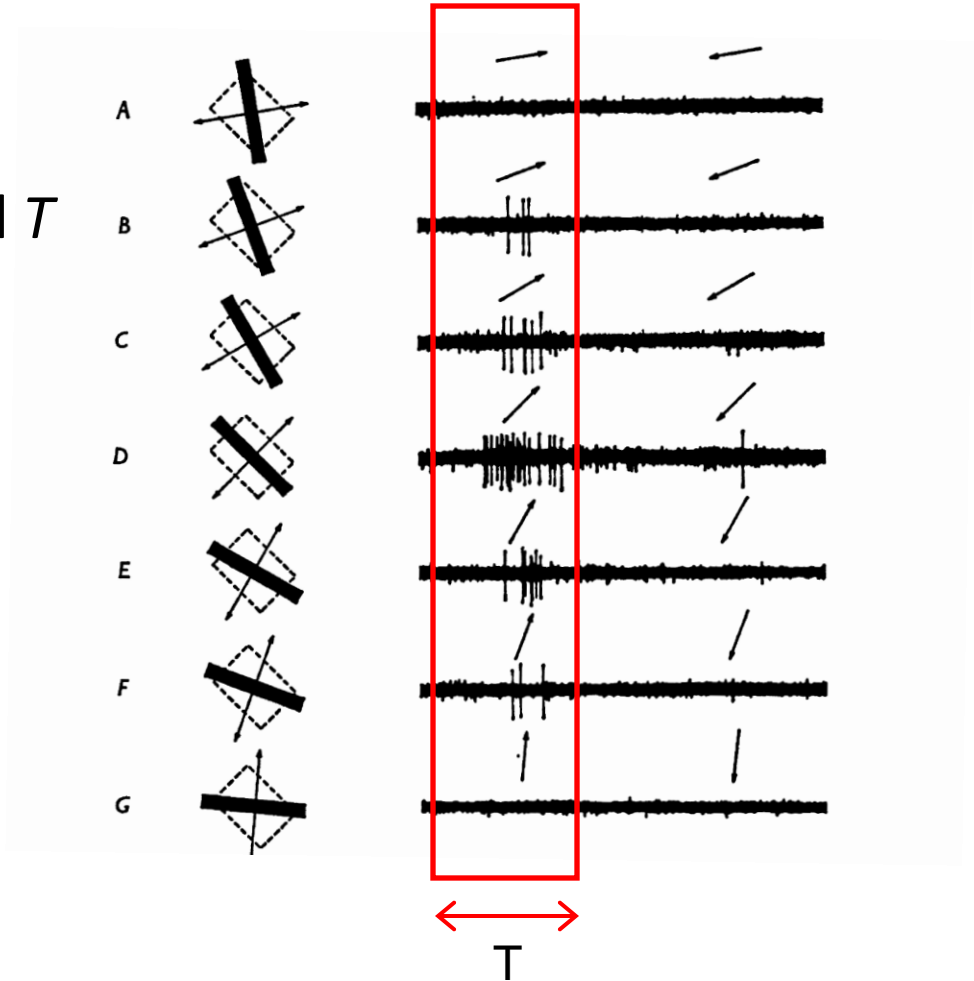
- concept: information encoded in **temporally precise spike times** and spike patterns across neurons
- fast information transmission through **coincident spiking** in neuronal assemblies
- encoding with few action potentials (sparse code) explores large coding space
- neuron acts as **coincidence detector**

Contra:

- little conclusive evidence
- single action potentials and coincident events vanish in the variable ongoing network activity

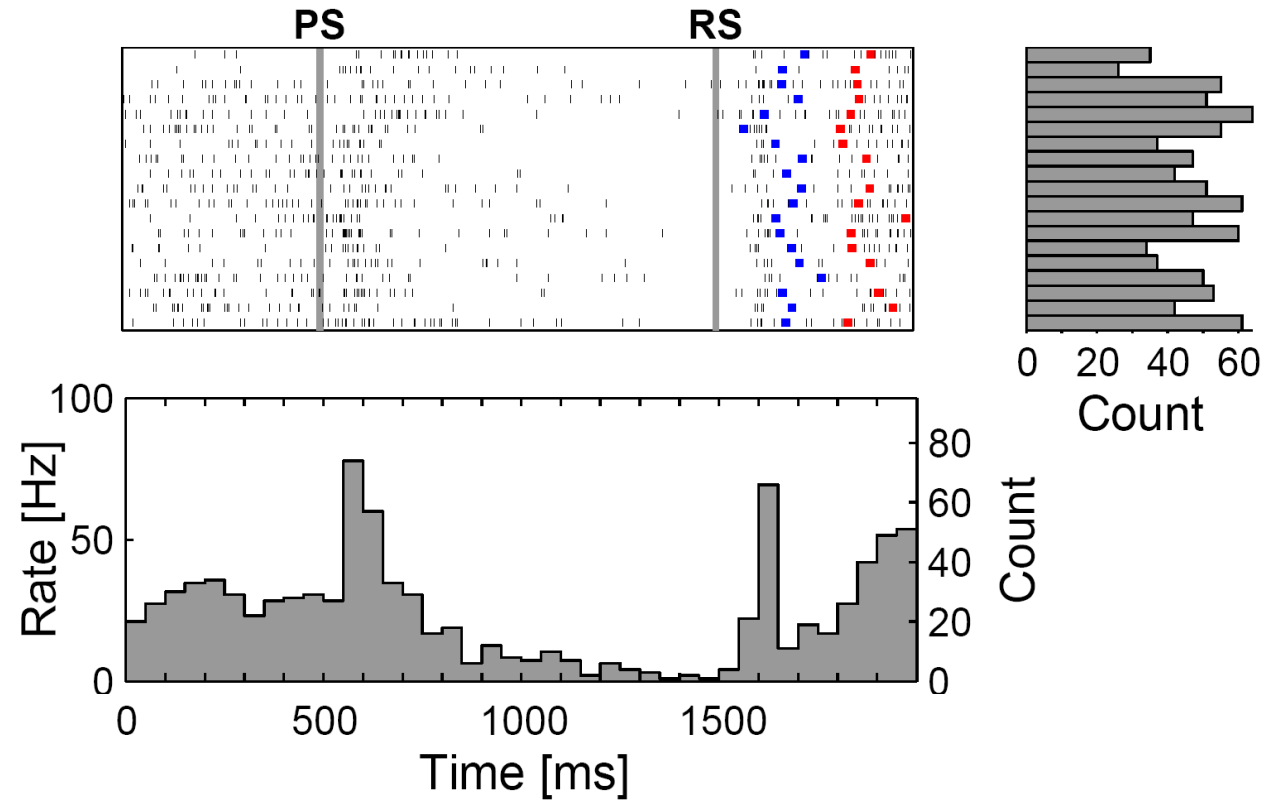
Rate code: concept and stimulus tuning

- spike count N in time interval T
- rate $r = N/T$



Hubel and Wiesel (1968) J Physiol 195: 215-43

Rate code: Time-varying rate estimate



Single unit activity from primary motor cortex of the monkey during repeated reaching movement
Data Curtsey: Alexa Riehle, CNRS, Marseille

Rate Code vs. Temporal Code

Rate Code

- concept: information encoded in neuronal **firing rate**
- **population code** permits encoding of precise information
- **redundancy** in large populations permits fast transmission
- neuron acts as '**Integrator**'

Contra:

- rate coding requires integration time (it is slow)
- large numbers of action potentials consume a large amount of energy
- combinatorial explosion in large coding space (grand mother cells)

Temporal Code

- concept: information encoded in **temporally precise spike times** and spike patterns across neurons
- fast information transmission through **coincident spiking** in neuronal assemblies
- encoding with few action potentials (sparse code) explores large coding space
- neuron acts as **coincidence detector**

Contra:

- little conclusive evidence
- single action potentials and coincident events vanish in the variable ongoing network activity

Rate Code vs. Temporal Code

Rate Code

- concept: information encoded in neuronal **firing rate**
- **population code** permits encoding of precise information
- **redundancy** in large populations permits fast transmission
- neuron acts as '***Integrator***'

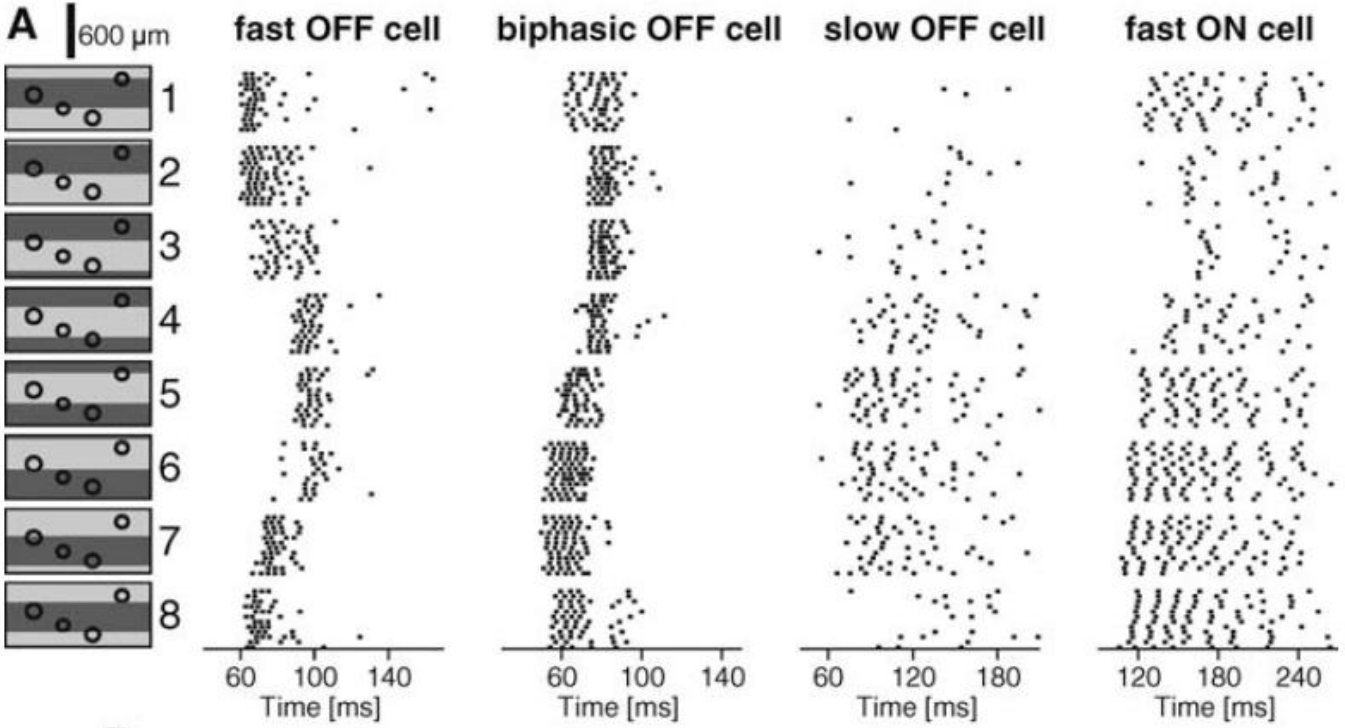
Contra:

- rate coding requires integration time (it is slow)
- large numbers of action potentials consume a large amount of energy
- combinatorial explosion in large coding space (grand mother cells)

Temporal Code

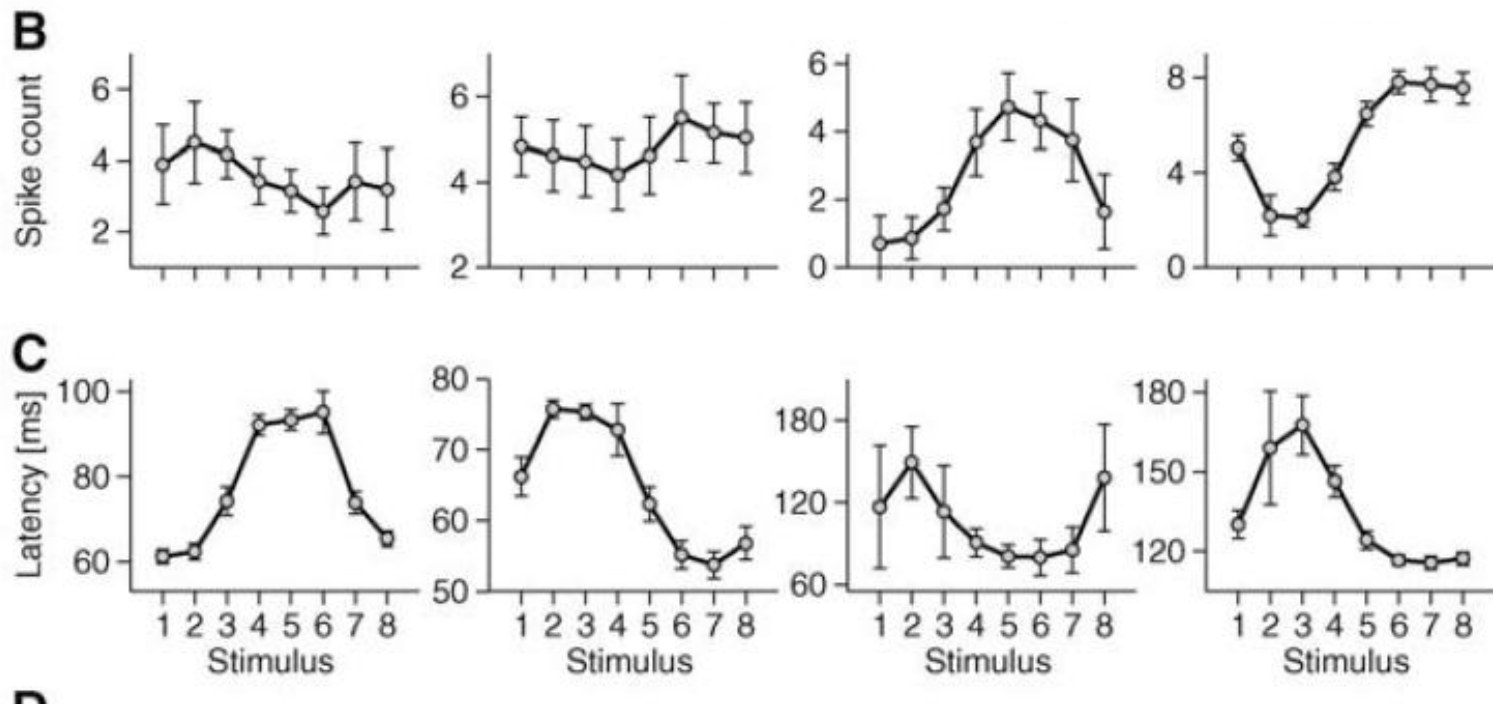
- concept: information encoded in **temporally precise spike times** and spike patterns across neurons
- fast information transmission through **coincident spiking** in neuronal assemblies
- encoding with few action potentials (sparse code) explores large coding space
- neuron acts as **coincidence detector**

Temporal code: experimental evidence I



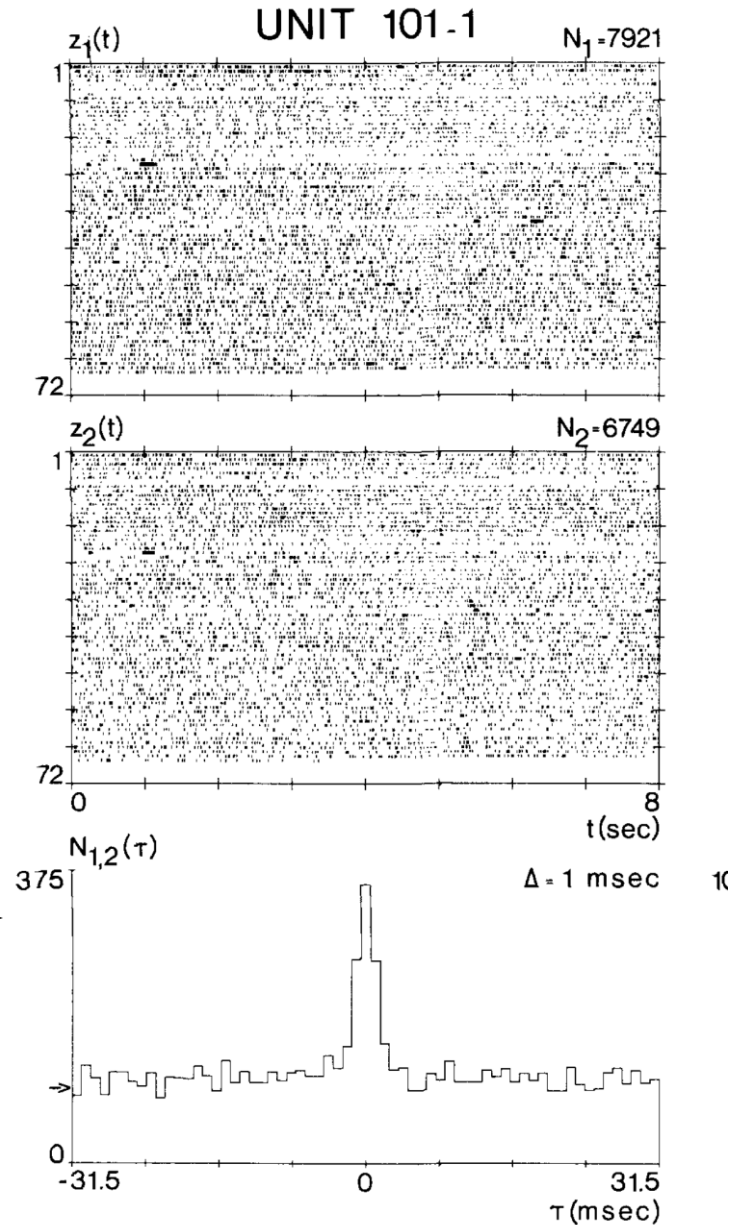
Gollisch and Meister (2008) Science 319

Temporal code: experimental evidence I



Temporal code: experimental evidence II

single unit recorded in the auditory nerve of the cat

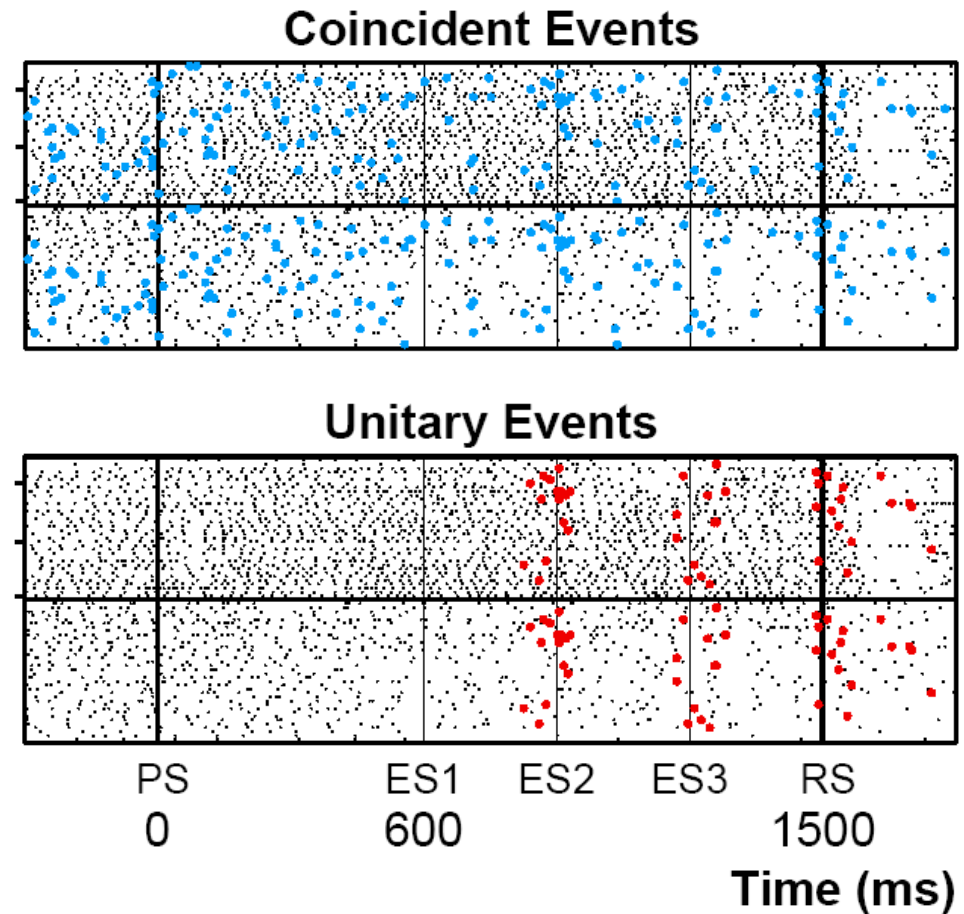


cross-correlogram of trials 1 + 2 →

Aertsen, Smolders & Johannesma (1979) *Biol. Cyber.* 32, 175-185

Temporal code: experimental evidence III

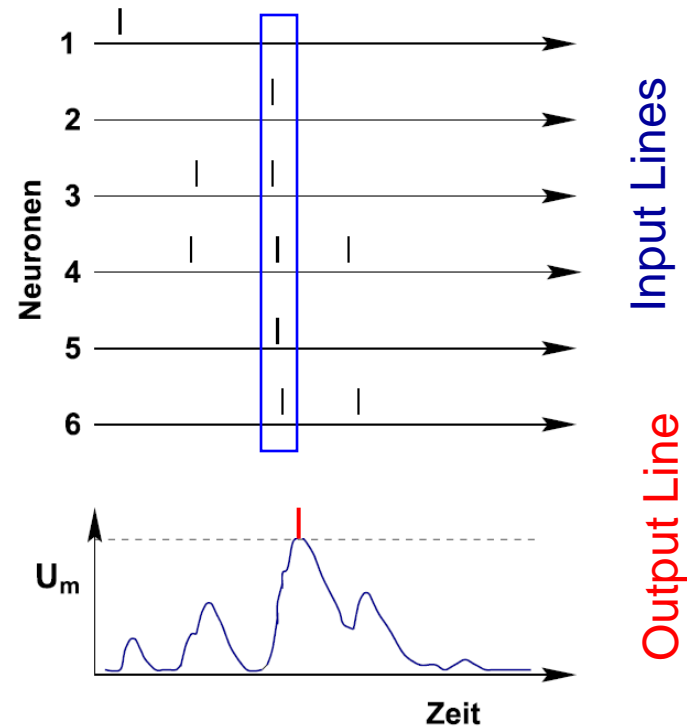
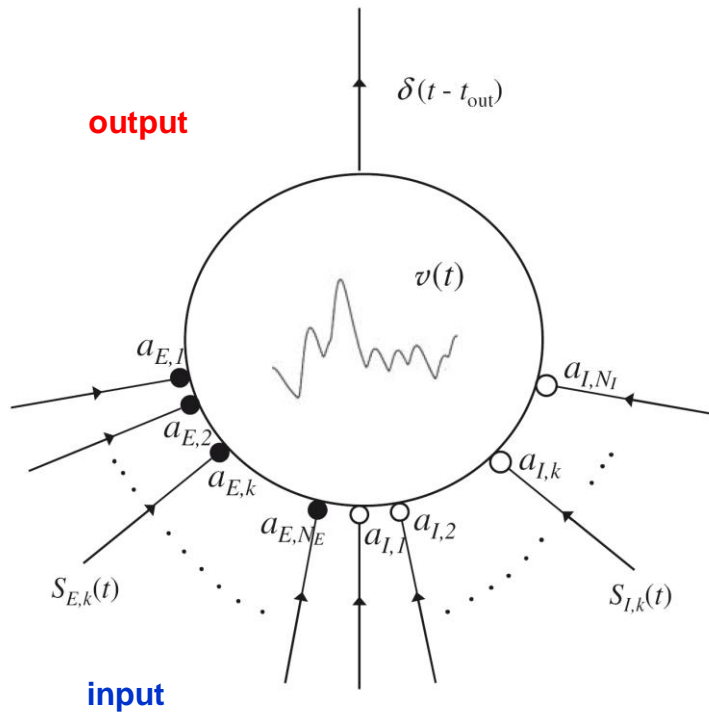
significant coincident spiking in motor cortical units related to expectation



Riehle, Grün, Diesmann, Aertsen (1997) Science 278, 1950-53

Temporal code: neuron acts as coincidence detector

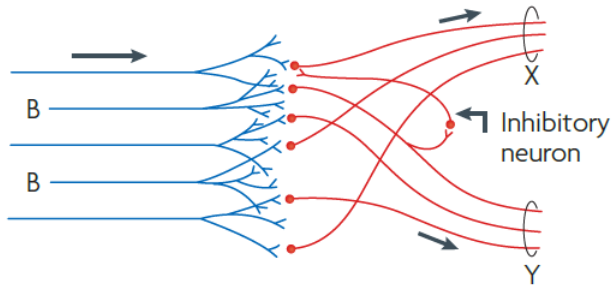
- **coincident** excitatory synaptic **inputs** are translated into a **single spike output**



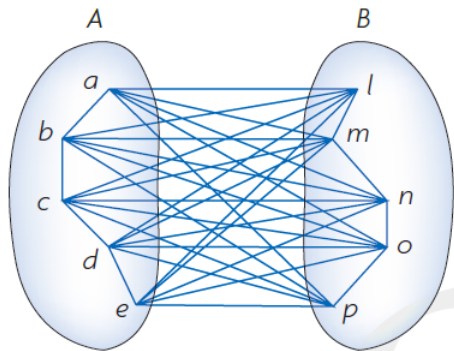
Burkitt (2006) *Biol. Cyber.* 95

Temporal code: 'synfire chain model'

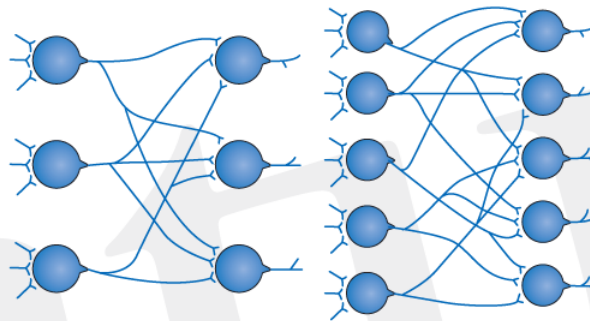
a



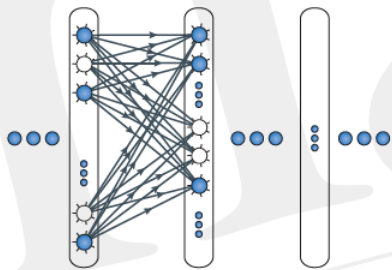
b



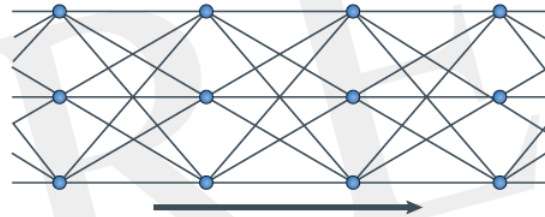
c



d



f

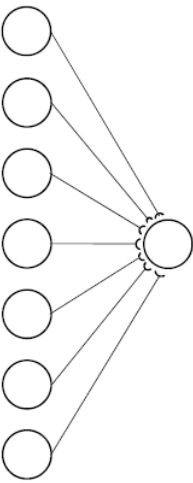


- a) Hebb 1949
- b) James 1890
- c) Abeles 1991
- d) Diesmann 1999
- f) Griffith 1963

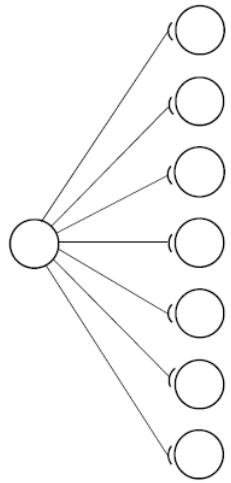
Kumar, Rotter, Aertsen (2010) Nat Rev Neurosci

Temporal code: ‚synfire chain model‘

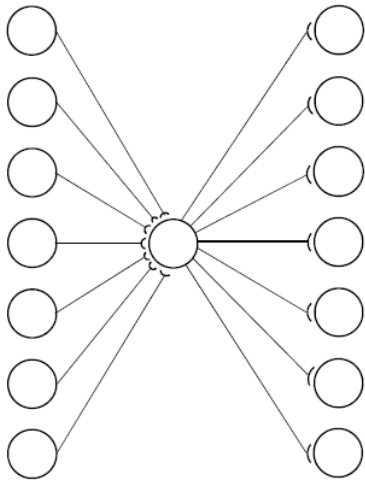
Konvergenz



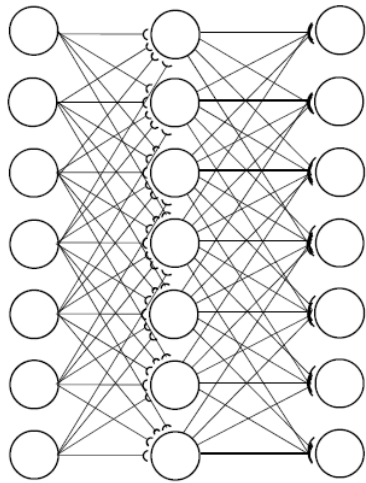
Divergenz



Konvergenz+Divergenz



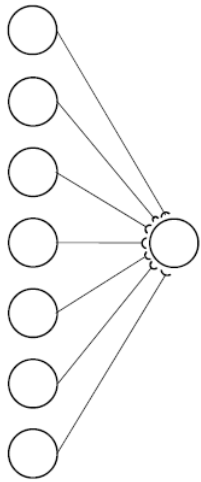
Konvergenz+Divergenz
(alle Neurone)



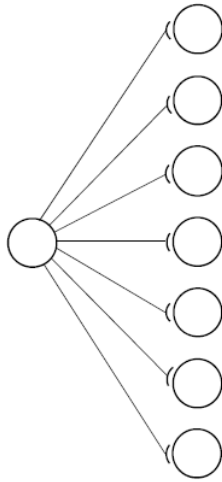
Curtsey: Sonja Grün

Temporal code: ‚synfire chain model‘

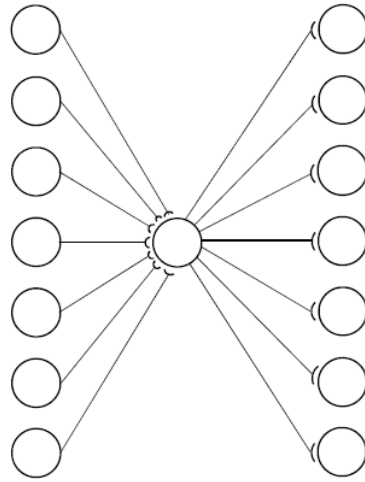
Konvergenz



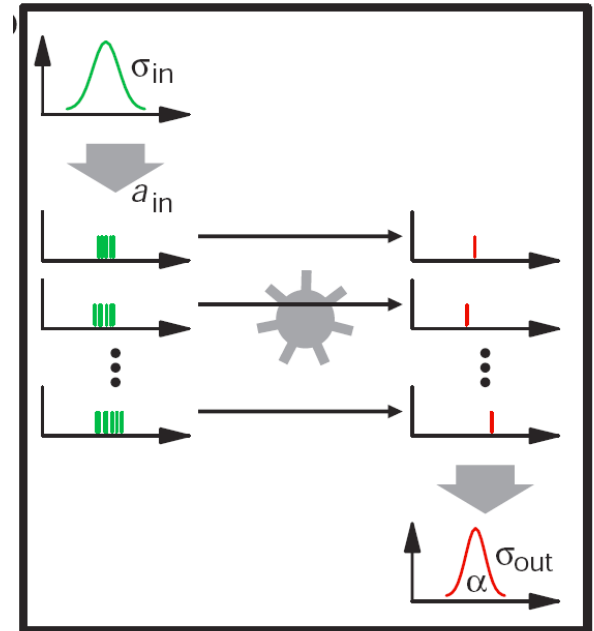
Divergenz



Konvergenz+Divergenz



Pulspaket Eingang



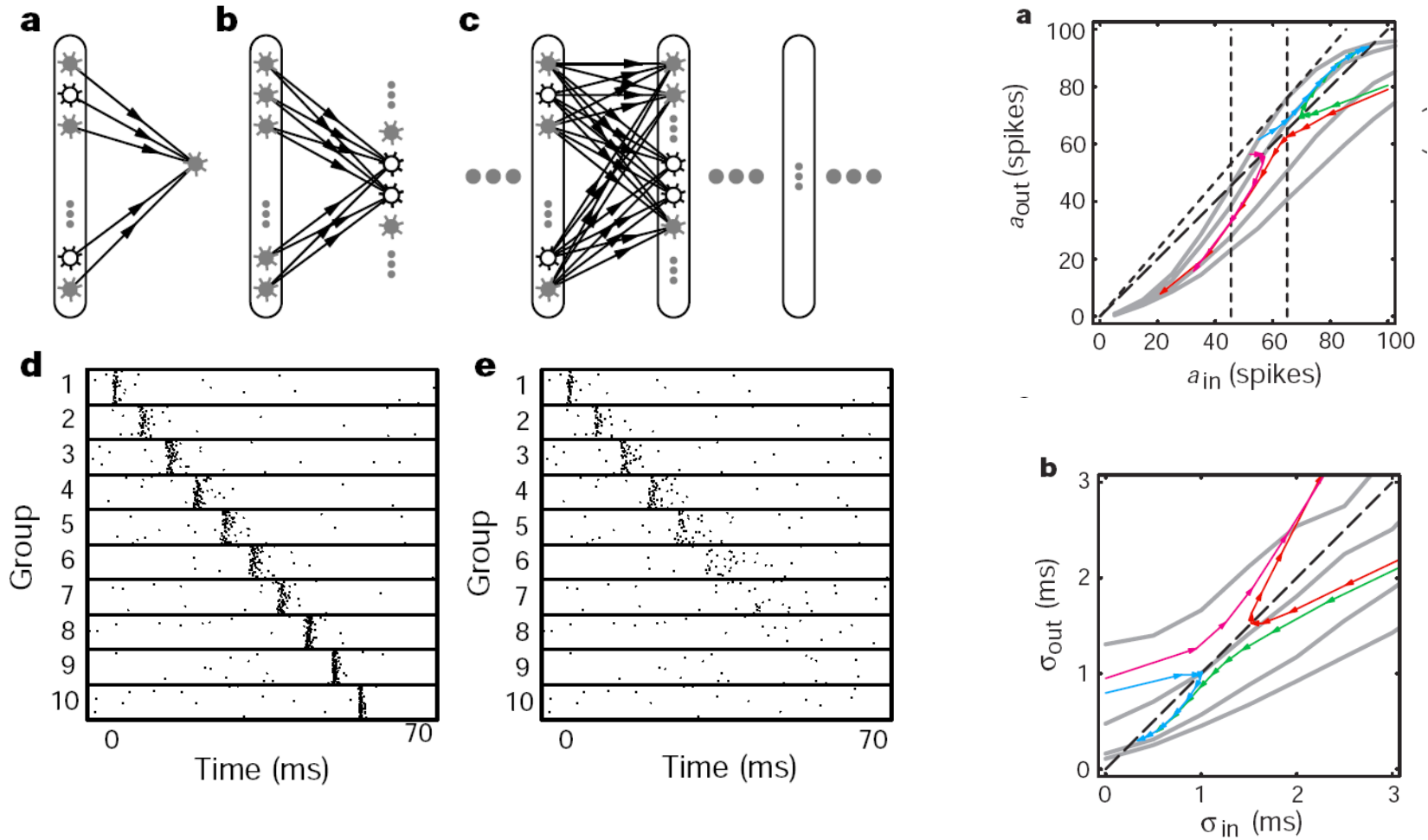
Diesmann et al. (1999) Nature 402: 529-532

pulse packet:

a = number of presynaptic spikes

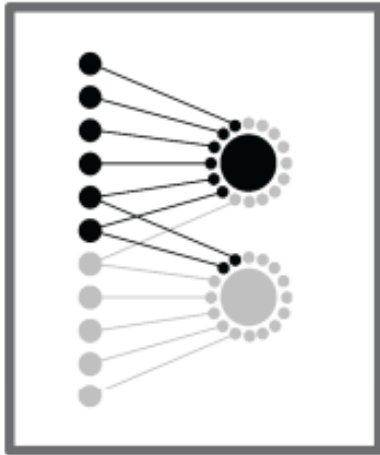
σ = temporal dispersion of spikes

Temporal code: 'synfire chain model'

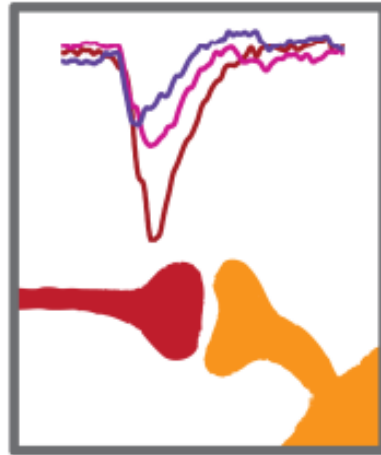


Diesmann et al. (1999) Nature 402: 529-532

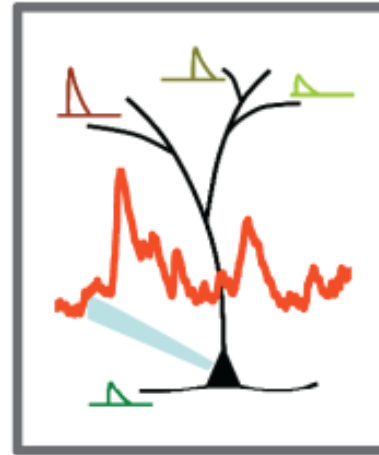
Temporal Code: are neurons precise enough ?



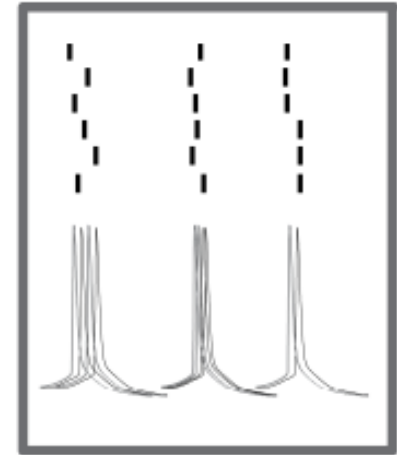
network motif



synaptic transmission



dendritic integration

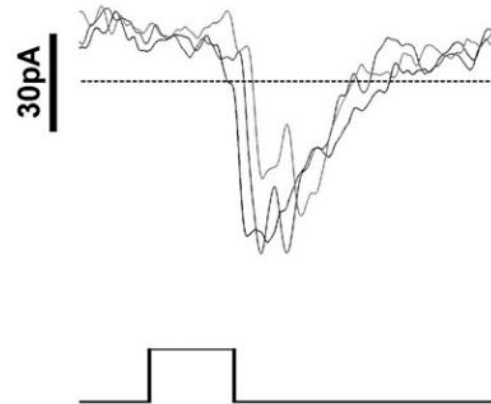
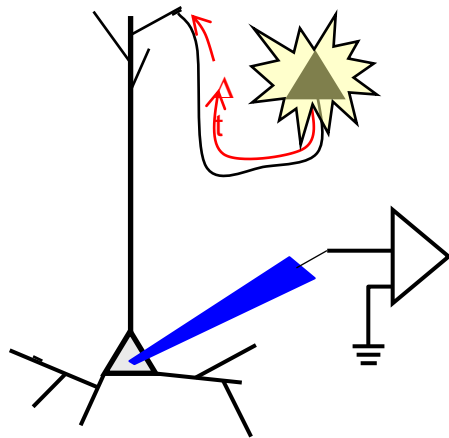


spike generation

Boucsein et al. (2011) Frontiers in Neuroscience 5:32

Temporal Code: are neurons precise enough ?

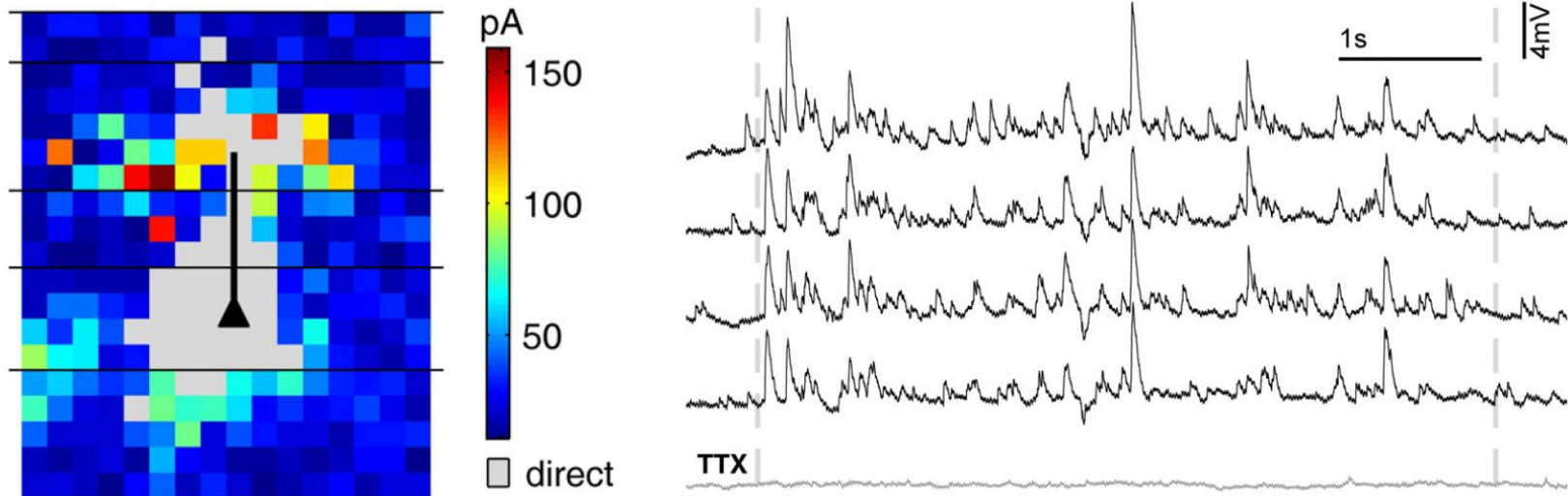
- ▶ high **reliability** of synaptic transmission (> 90%)
- ▶ high **temporal precision** across trials (jitter < 1ms)
- ▶ modest **amplitude variability** (CV ~ 0.25)



Nawrot et al. (2009) *Frontiers in Neural Circuits* 3:1

Temporal Code: are neurons precise enough ?

- ▶ dendritic generation is **temporally precise** and **reliable**



Nawrot et al. (2009) Frontiers in Neural Circuits 3:1

Temporal Code: are neurons precise enough ?

- ▶ spike generation is **temporally precise** and **reliable**

Science 268: 1503-1506 (1995)

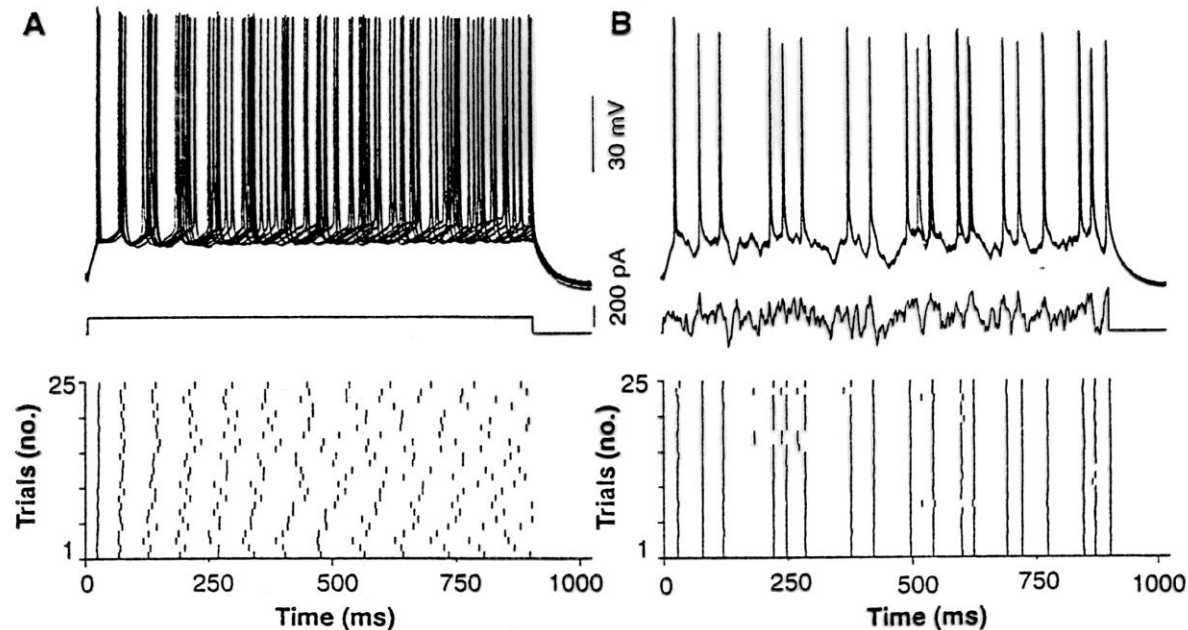


Fig. 1. Reliability of firing patterns of cortical neurons evoked by constant and fluctuating current. **(A)** In this example, a superthreshold dc current pulse (150 pA, 900 ms; middle) evoked trains of action potentials (approximately 14 Hz) in a regular-firing layer-5 neuron. Responses are shown superimposed (first 10 trials, top) and as a raster plot of spike times over spike times (25 consecutive trials, bottom). **(B)** The same cell as in **(A)** was again stimulated repeatedly, but this time with a fluctuating stimulus [Gaussian white noise, $\mu_s = 150$ pA, $\sigma_s = 100$ pA, $\tau_s = 3$ ms; see (14)].

Mainen & Sejnowski (1995) Science 268

Temporal Code: are neurons precise enough ?

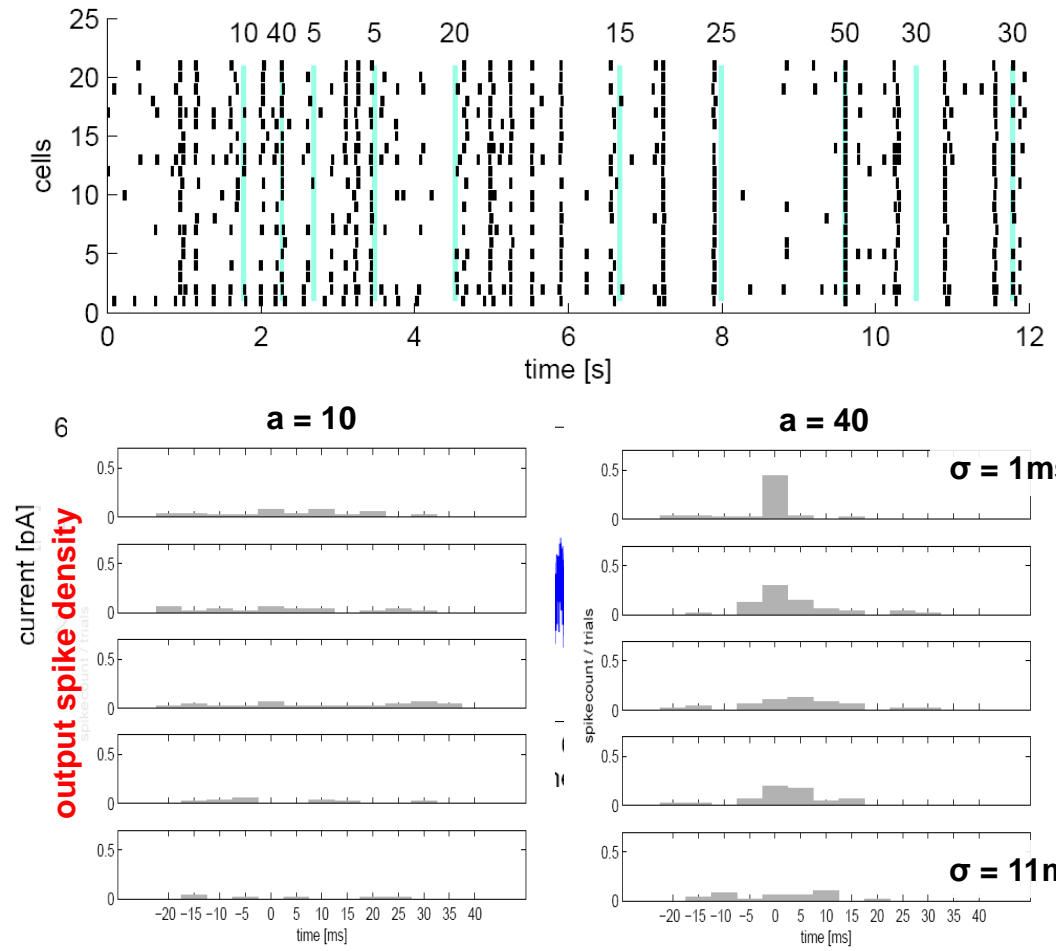


Abbildung 3.8: PP 10 mit σ von 1-11ms

Abbildung 3.11: PP 40 mit σ von 1-11ms

Susanne Reichinnek (2007) Diplomarbeit

Rate Code vs. Temporal Code

Rate Code

- concept: information encoded in neuronal **firing rate**
- **population code** permits encoding of precise information
- **redundancy** in large populations permits fast transmission
- neuron acts as '***Integrator***'

Contra:

- rate coding requires integration time (it is slow)
- large numbers of action potentials consume a large amount of energy
- combinatorial explosion in large coding space (grand mother cells)

Temporal Code

- concept: information encoded in **temporally precise spike times** and spike patterns across neurons
- fast information transmission through **coincident spiking** in neuronal assemblies
- encoding with few action potentials (sparse code) explores large coding space
- neuron acts as **coincidence detector**

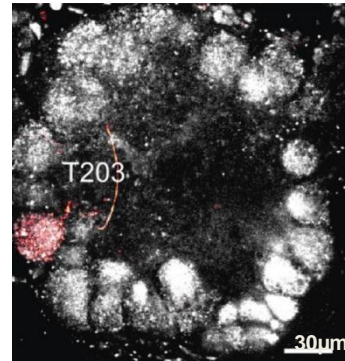
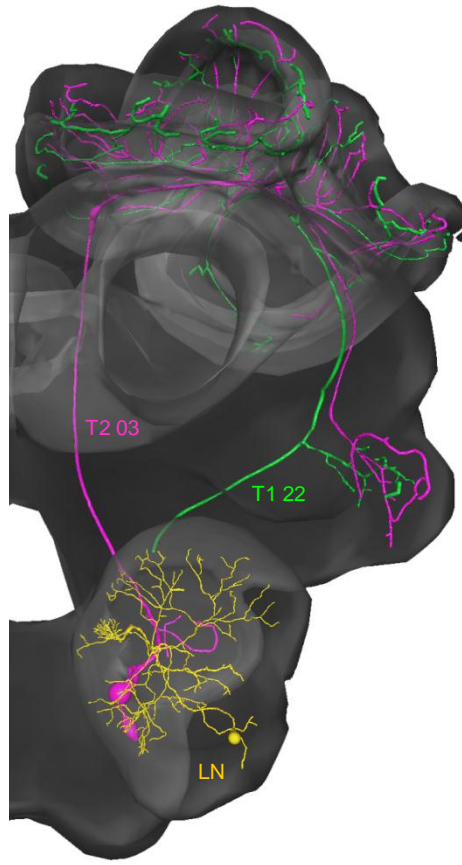
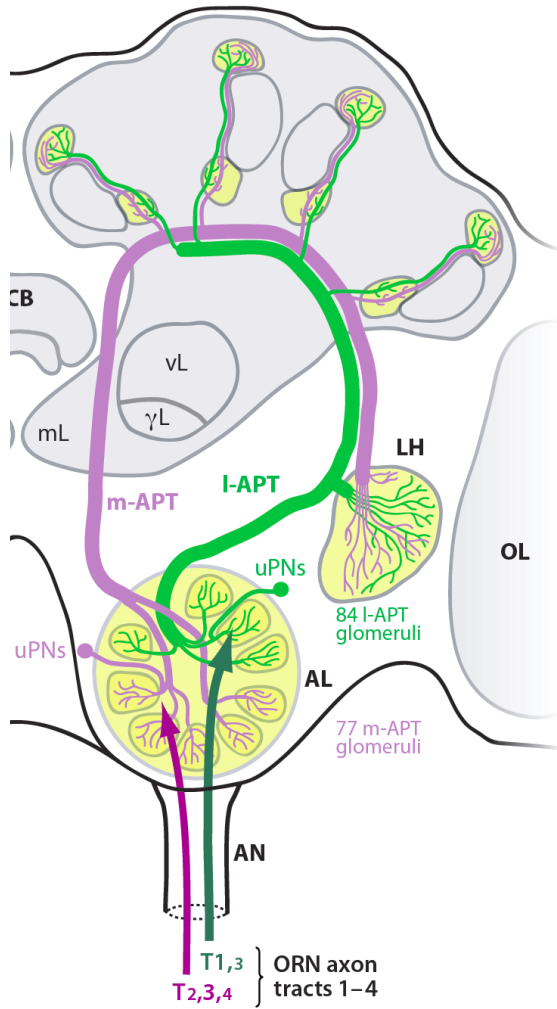
Contra:

- little conclusive evidence
- single action potentials and coincident events vanish in the variable ongoing network activity

Neural Coding II

- *Encoding – Recoding – Decoding*

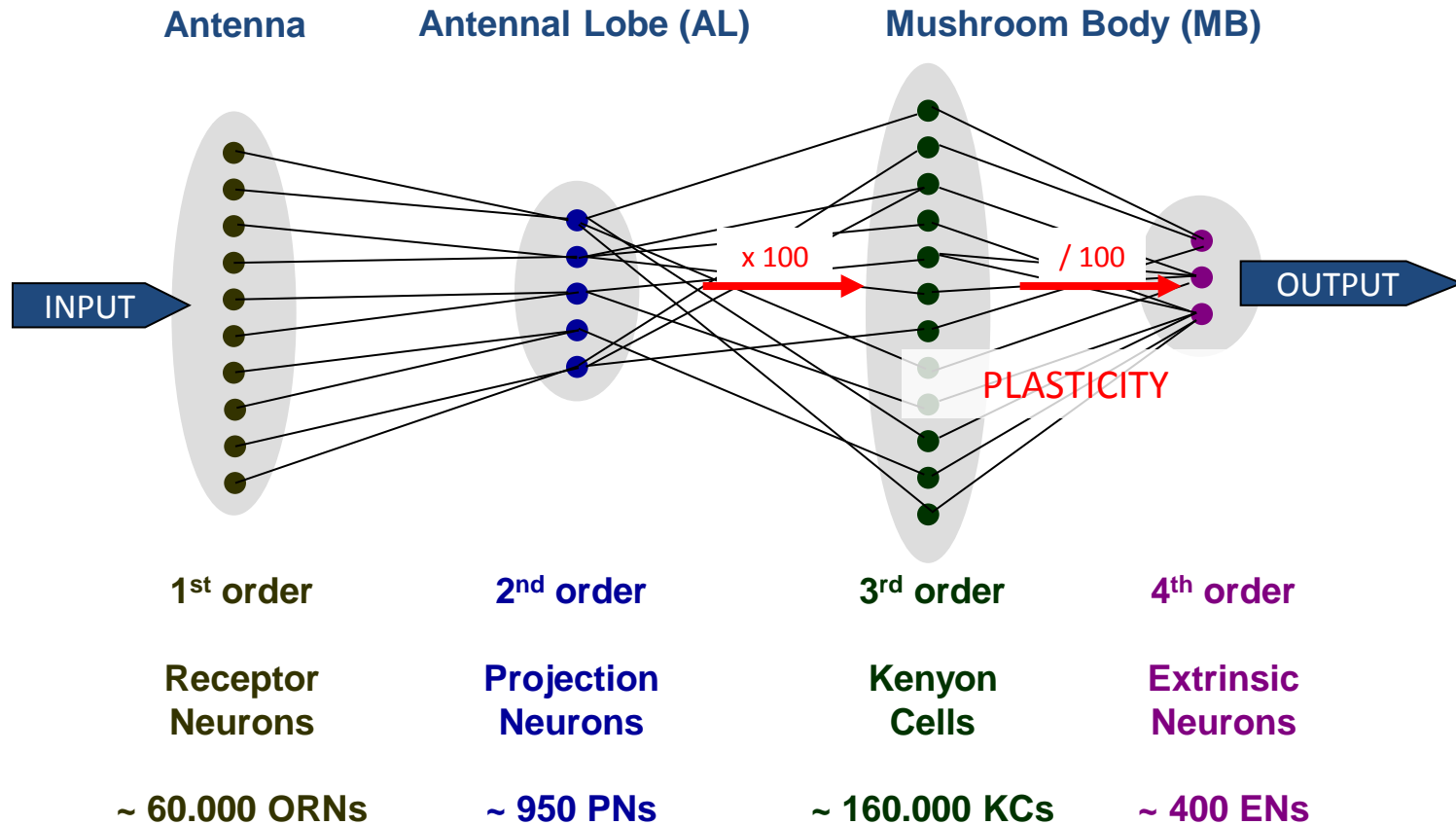
Olfactory system of the honeybee (insect)



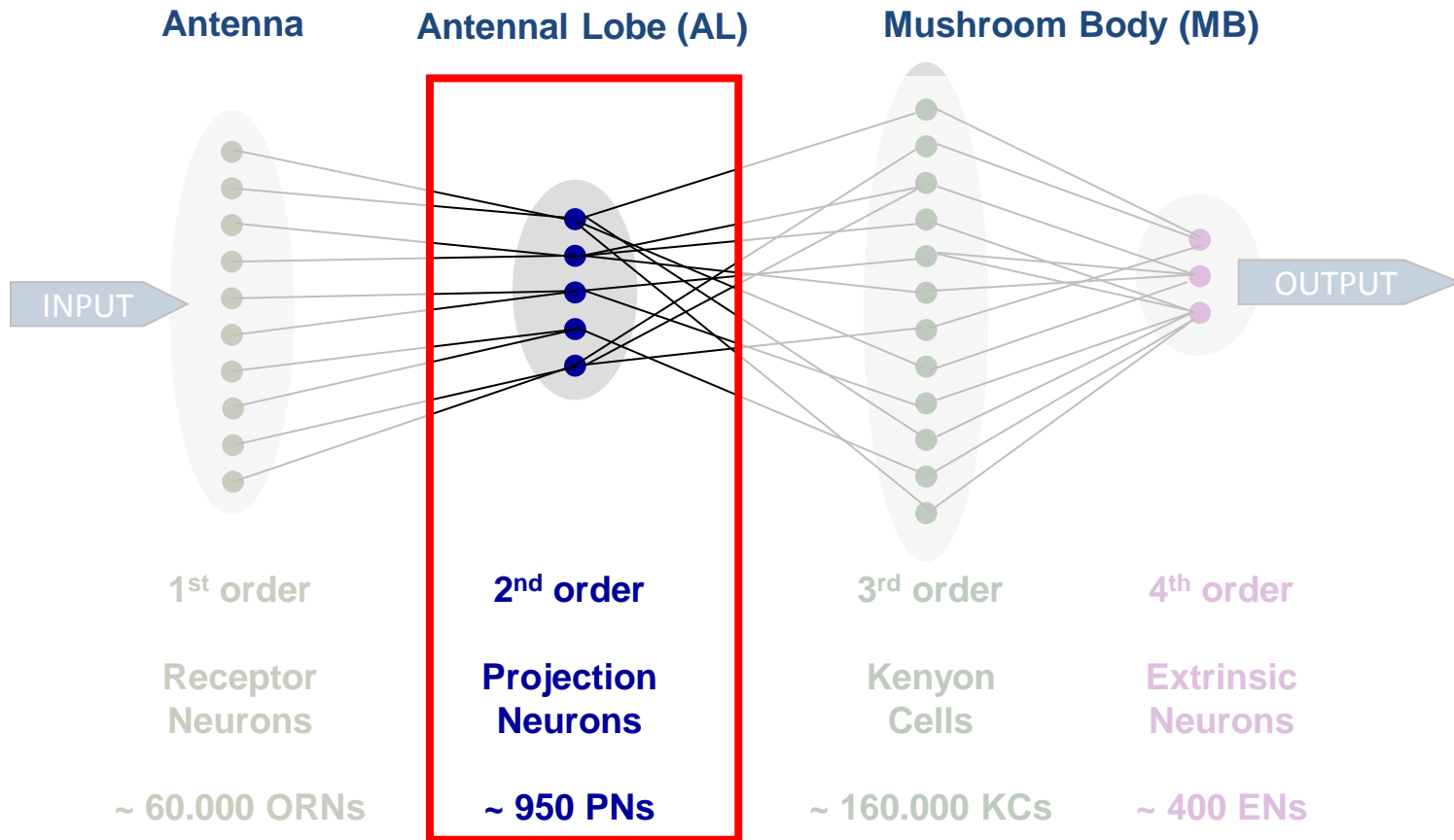
Galizia & Rössler (2009) *Annu. Rev. Entomol.* 55

Krofczik, Menzel & Nawrot (2008) *Frontiers Comp Neurosci* 2

Olfactory pathway in the honeybee (insect)



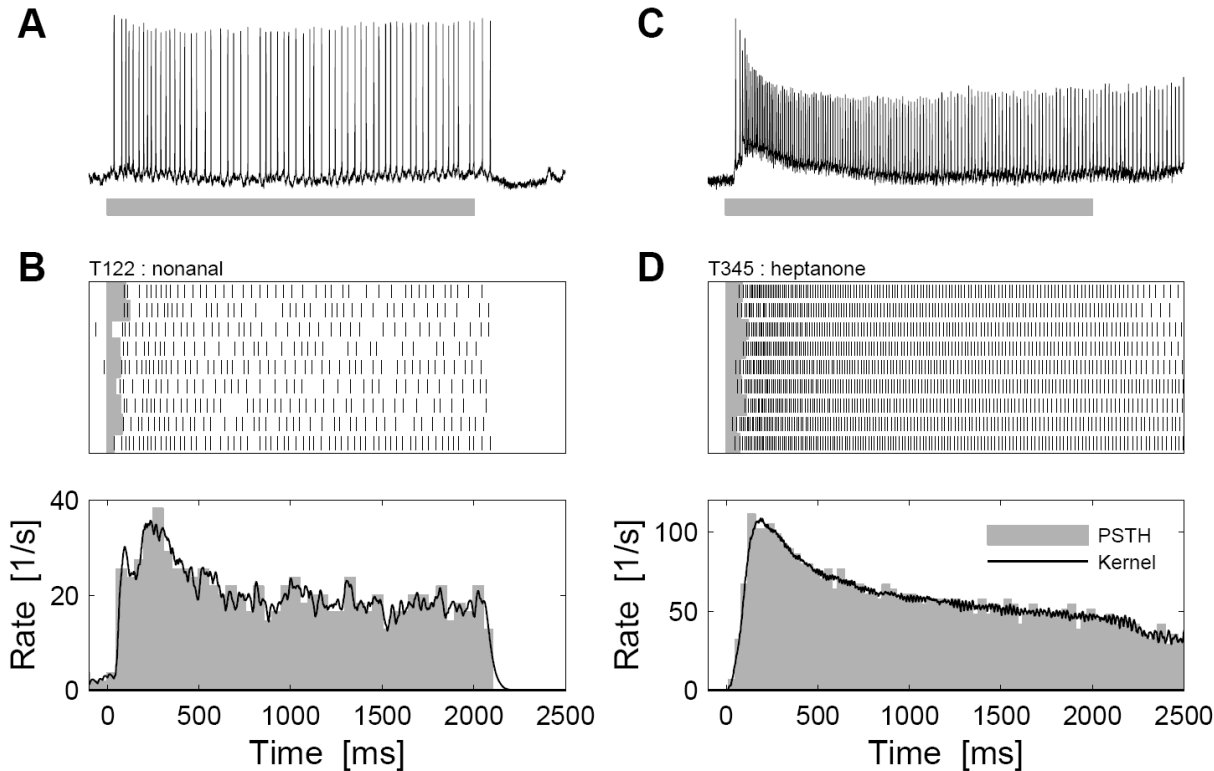
Encoding of odors in the antennal lobe



Krofczik, Menzel & Nawrot (2009) *Frontiers in Computational Neuroscience* 2

Encoding of odors in the antennal lobe : rate code

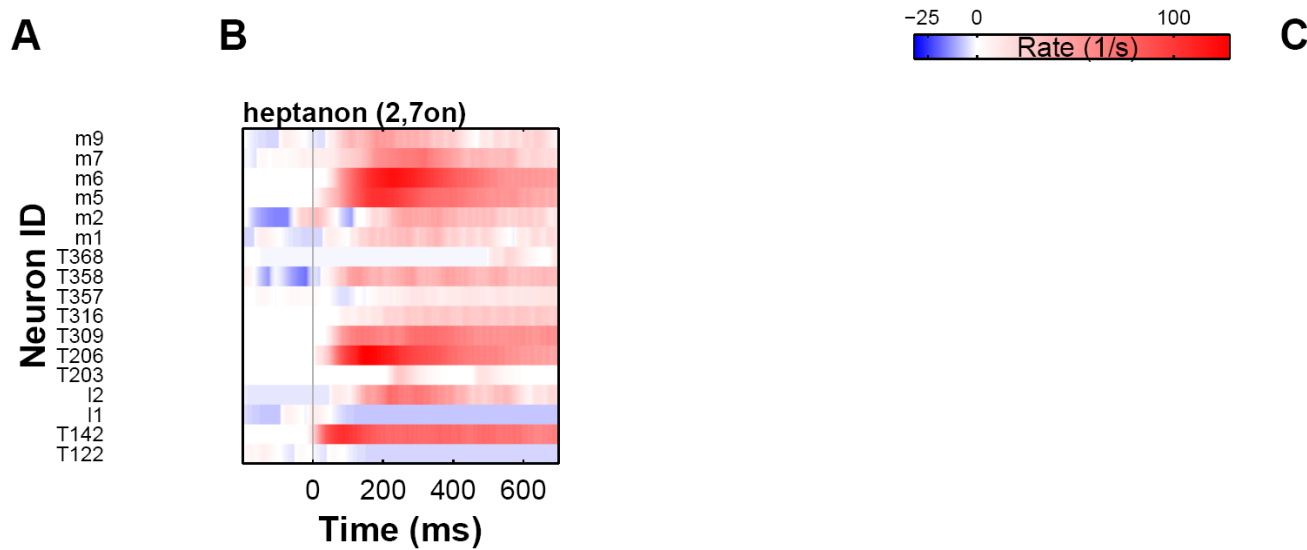
- ▶ Intracellular recordings from projection
- ▶ Reliable and stereotypic rate responses



Krofczik, Menzel & Nawrot (2009) *Frontiers Comp Neurosci* 2

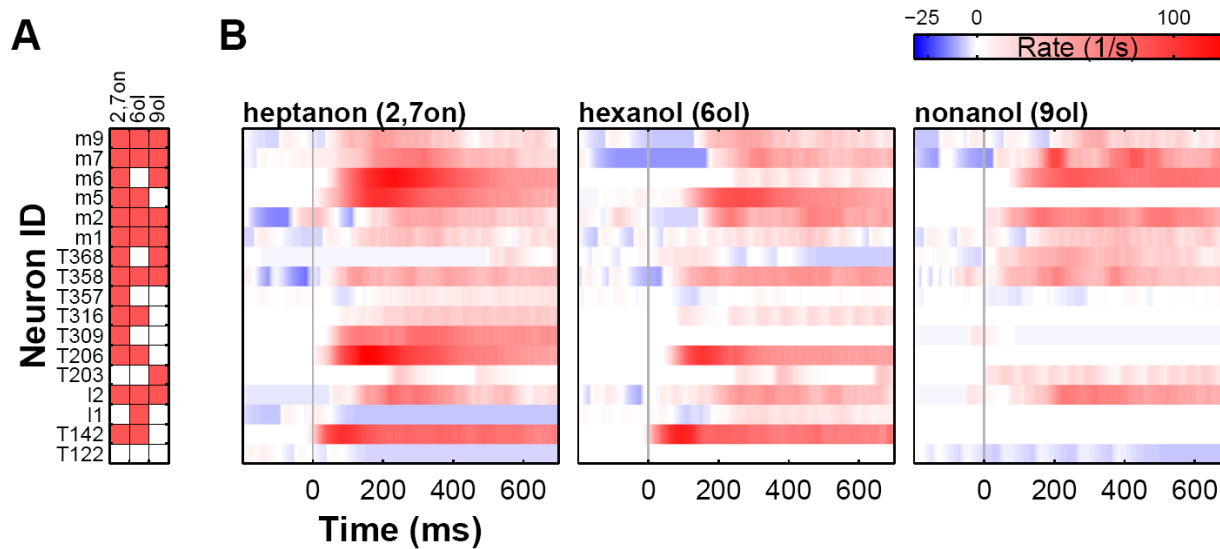
Encoding of odors in the antennal lobe : rate code

- ▶ >50% of PNs activated by single odor (**broad odor tuning**)



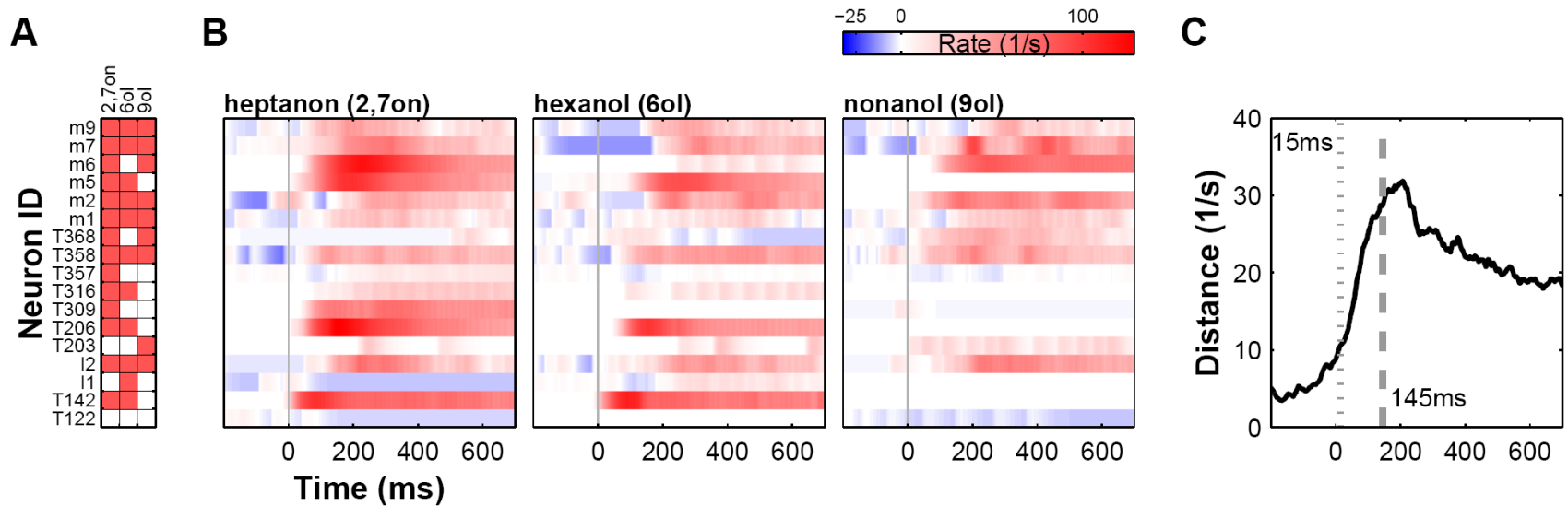
Encoding of odors in the antennal lobe : rate code

- ▶ >50% of PNs activated by single odor (**broad odor tuning**)
- ▶ odor specific binary activation pattern (**combinatorial code**)



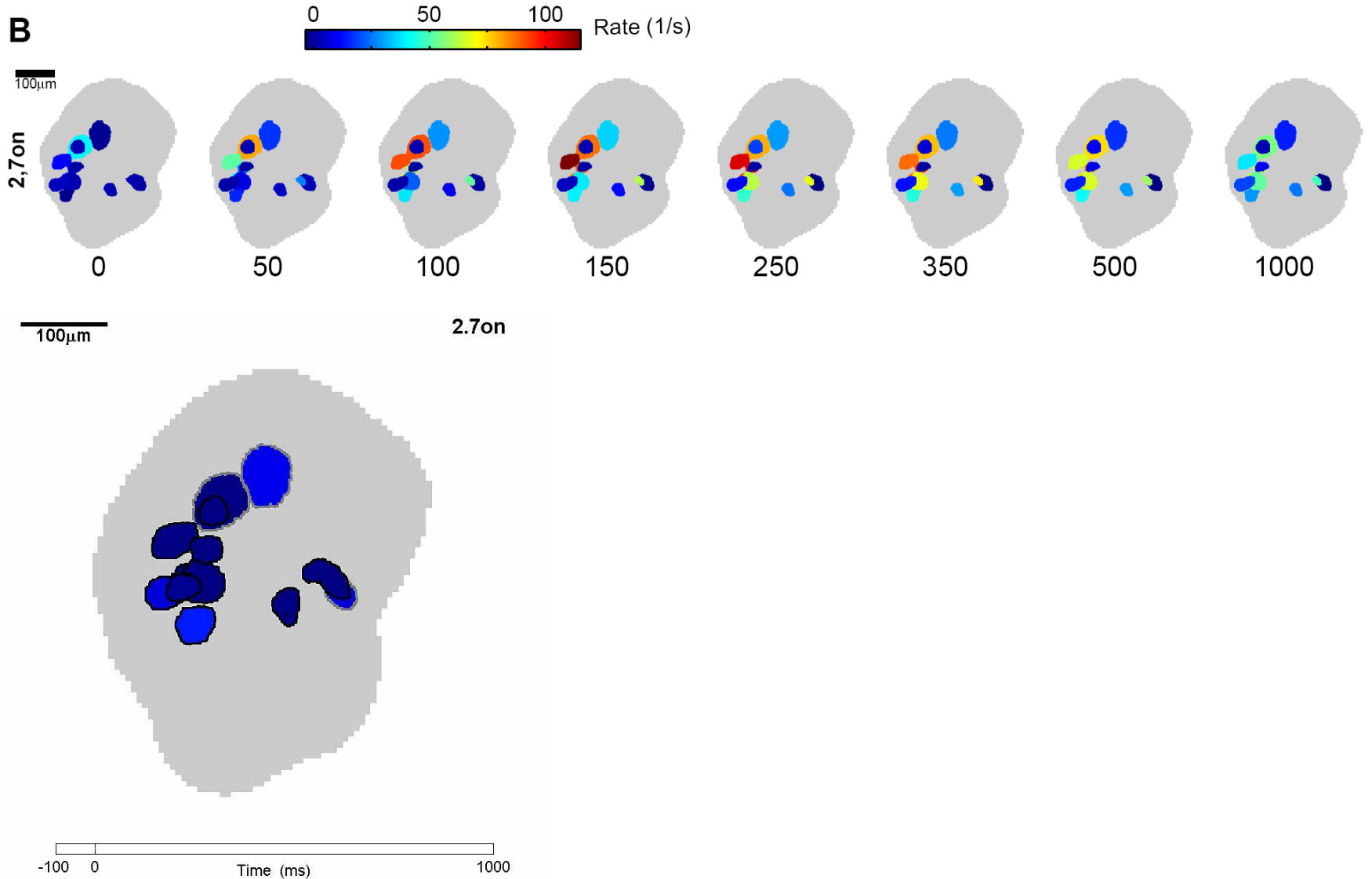
Encoding of odors in the antennal lobe : rate code

- ▶ >50% of PNs activated by single odor (**broad odor tuning**)
- ▶ odor specific binary activation pattern (**combinatorial code**)
- ▶ **rapid odor encoding** within tens of milliseconds

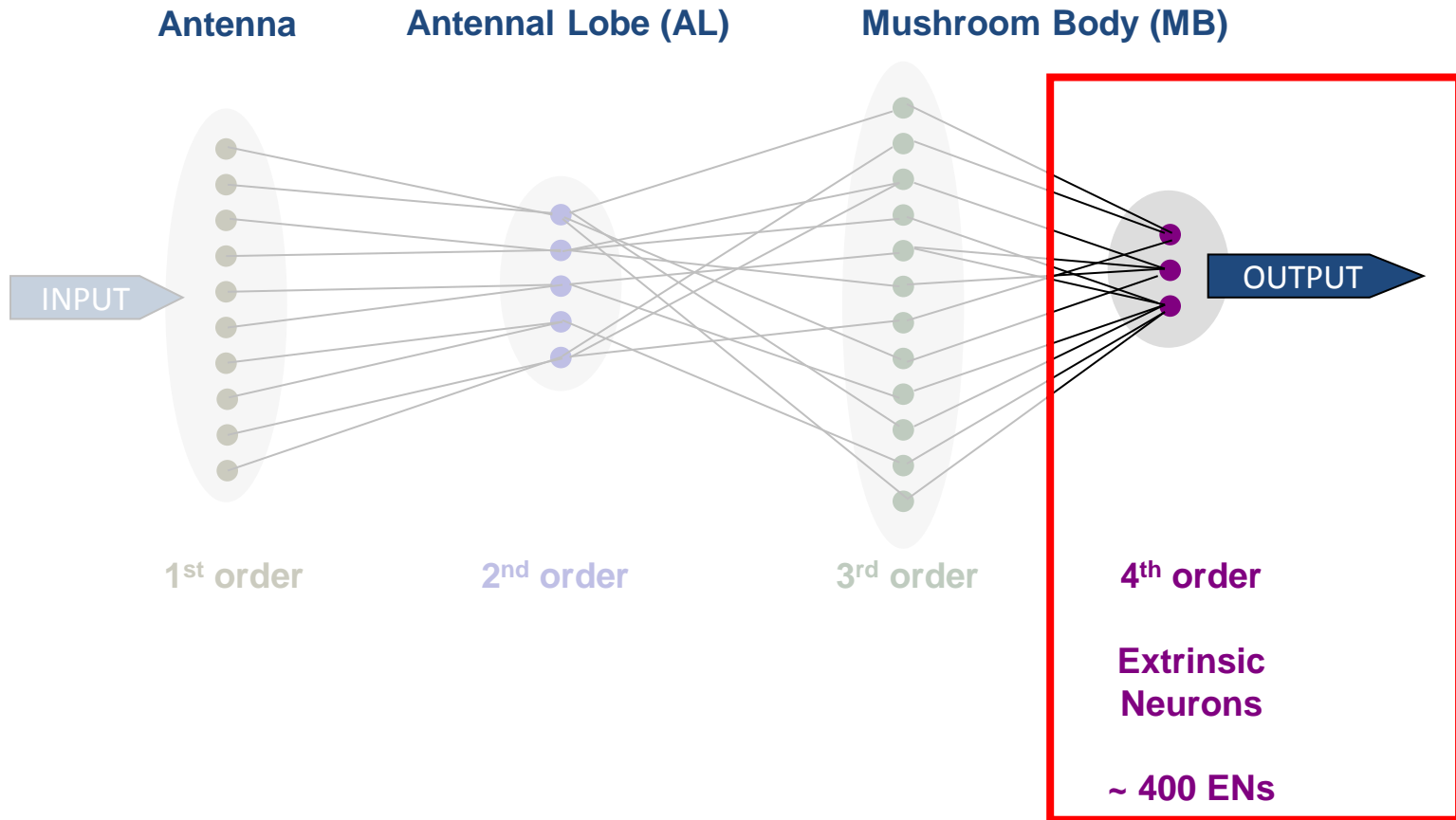


Krofczik, Menzel & Nawrot (2009) *Frontiers Comp Neurosci* 2

Encoding of odors in the antennal lobe : glomerular space

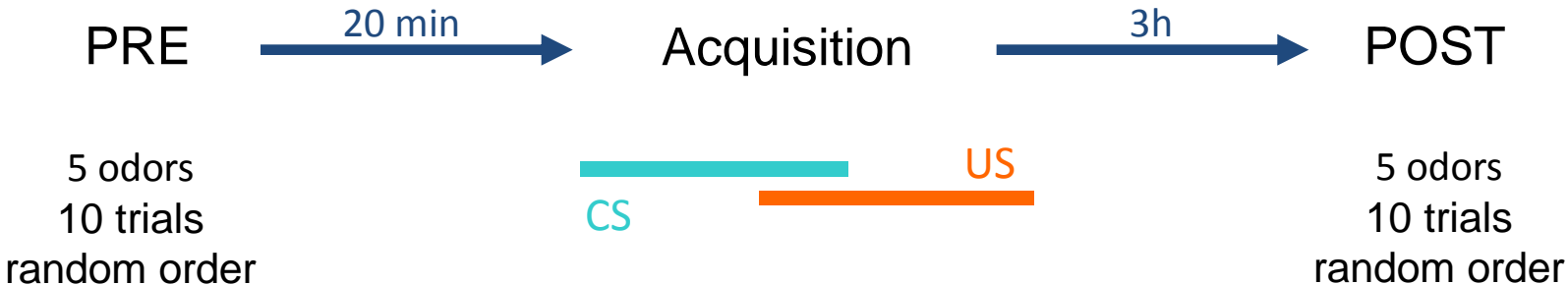


Recoding in the mushroom body



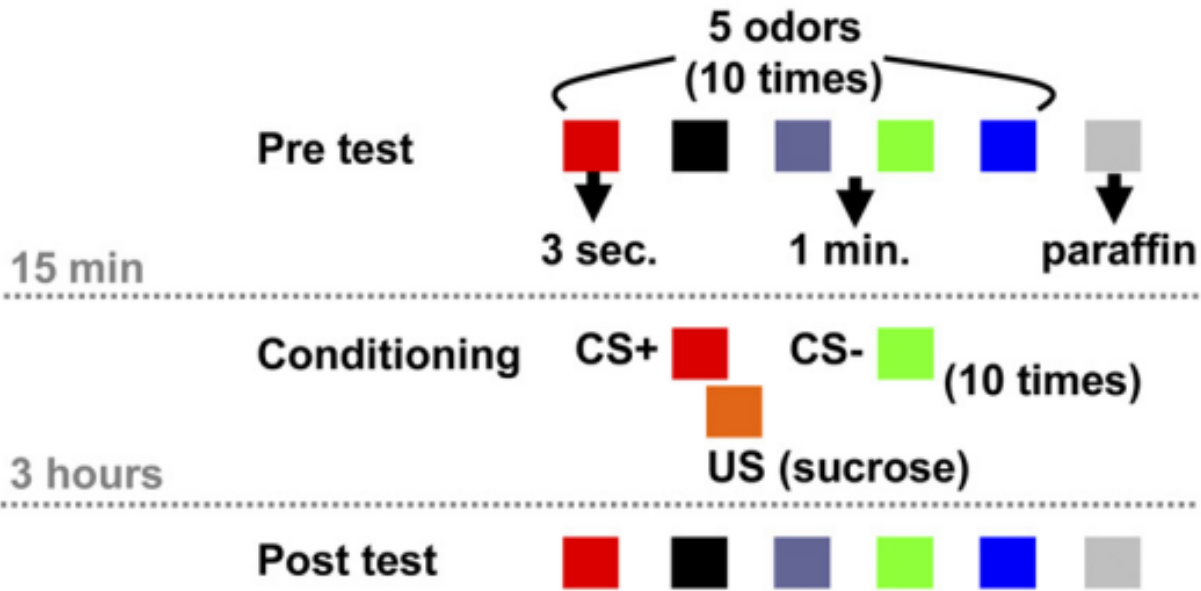
Strube-Bloss, Nawrot & Menzel (2011) J Neurosci 31

Classical conditioning: experimental paradigm



Experiments by Martin Strube-Bloss in the lab of Randolph Menzel

Classical conditioning: experimental paradigm

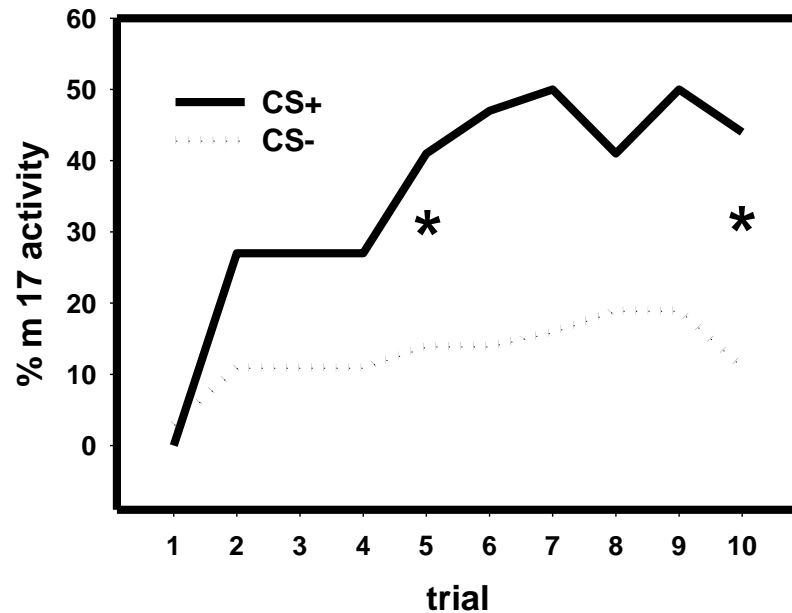


Strube-Bloss, Nawrot & Menzel (2011) J Neurosci 31

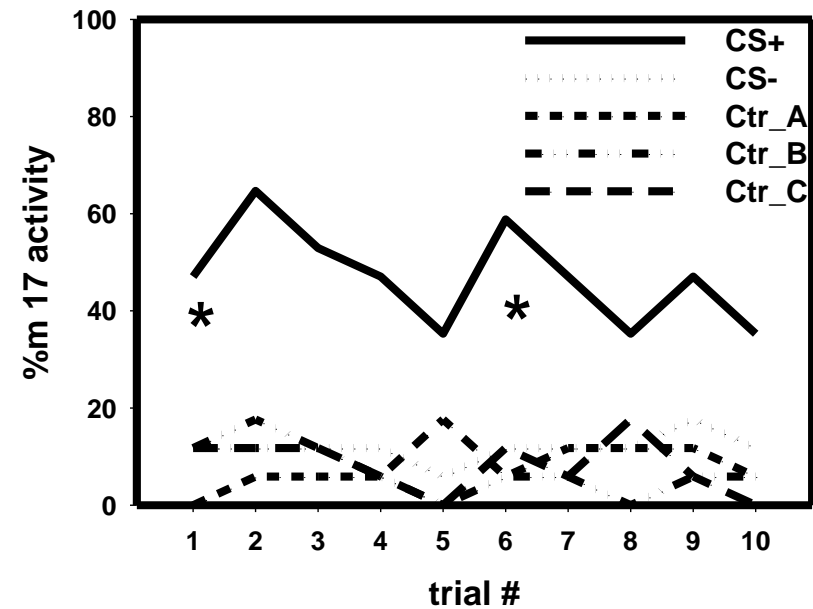
Classical conditioning : behavioral performance (group)

- ▶ Bees learn odor-reward association under experimental conditions

Acquisition [N=36]

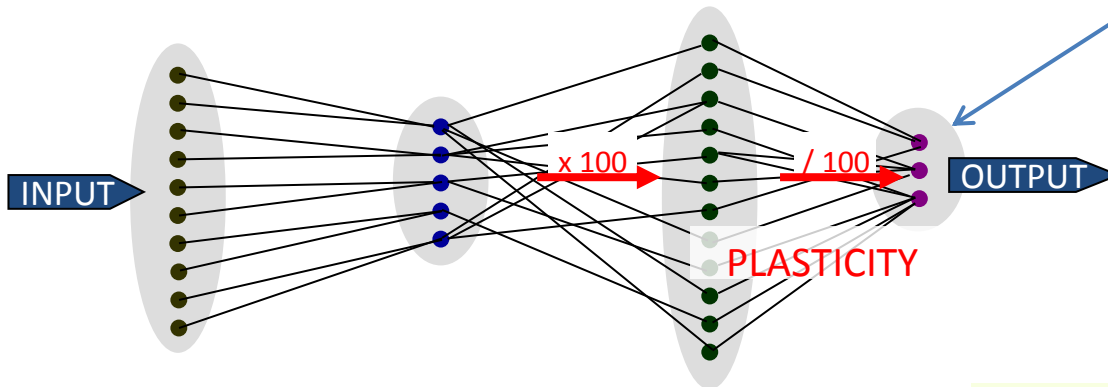
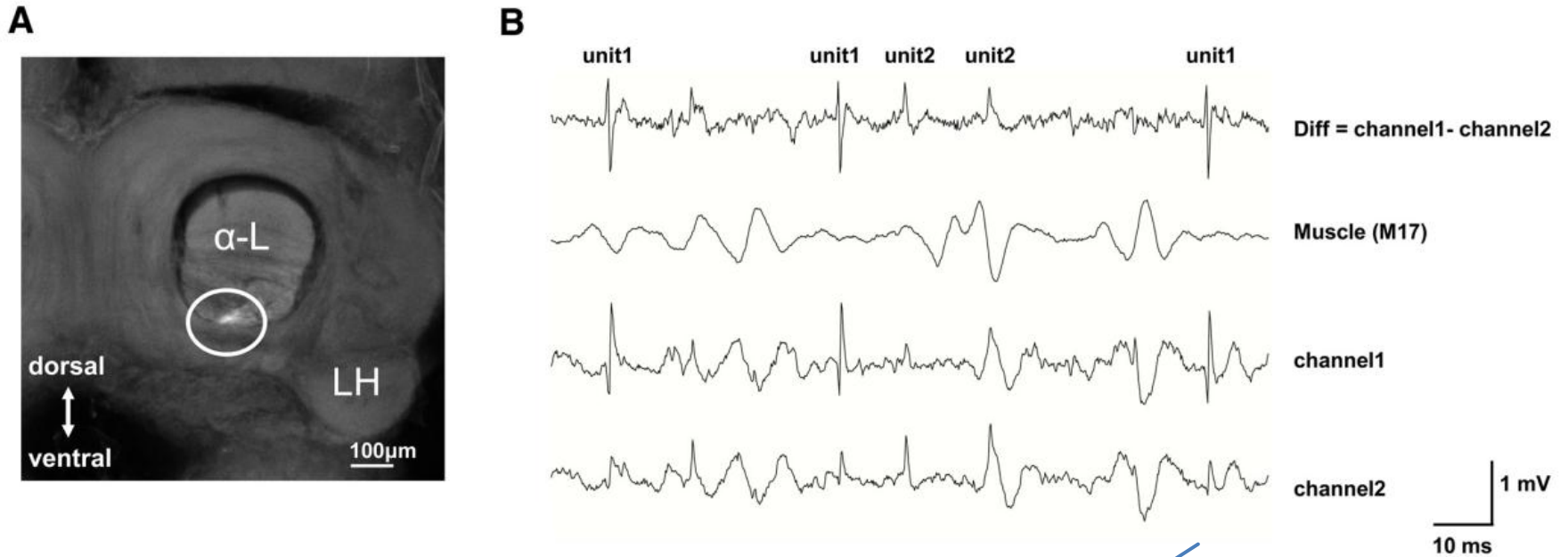


PostAcquisition_Test [N=17]



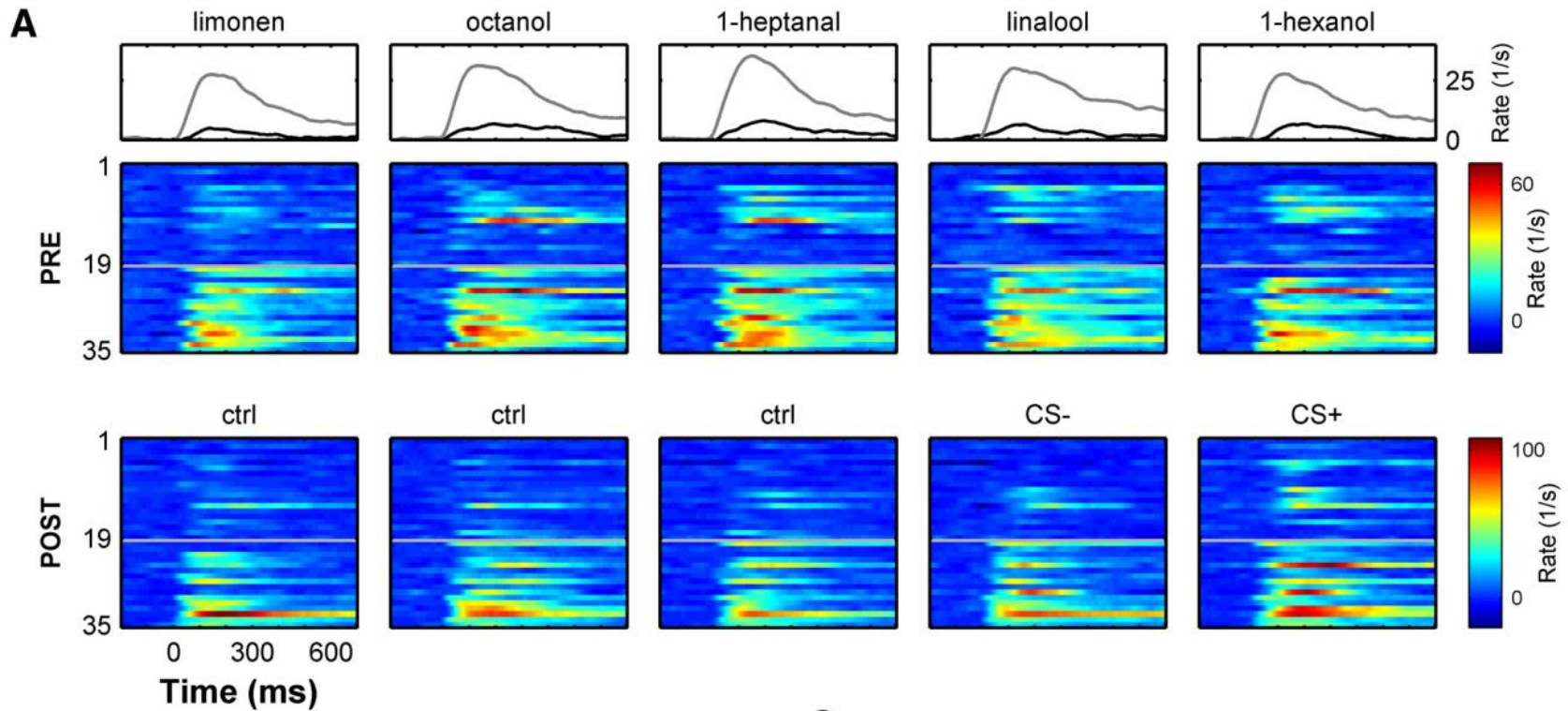
Strube-Bloss, Nawrot & Menzel (2011) J Neurosci 31

Single unit recording at mushroom body output



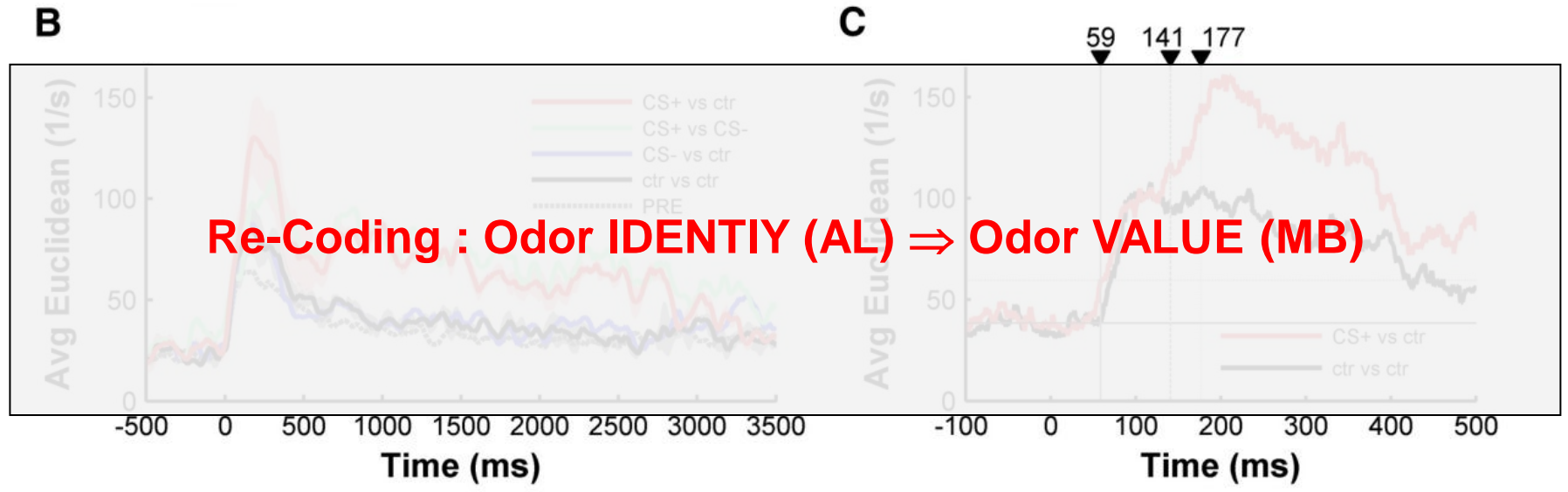
Strube-Bloss, Nawrot & Menzel (2011) *J Neurosci* 31

Odor VALUE coding at mushroom body output

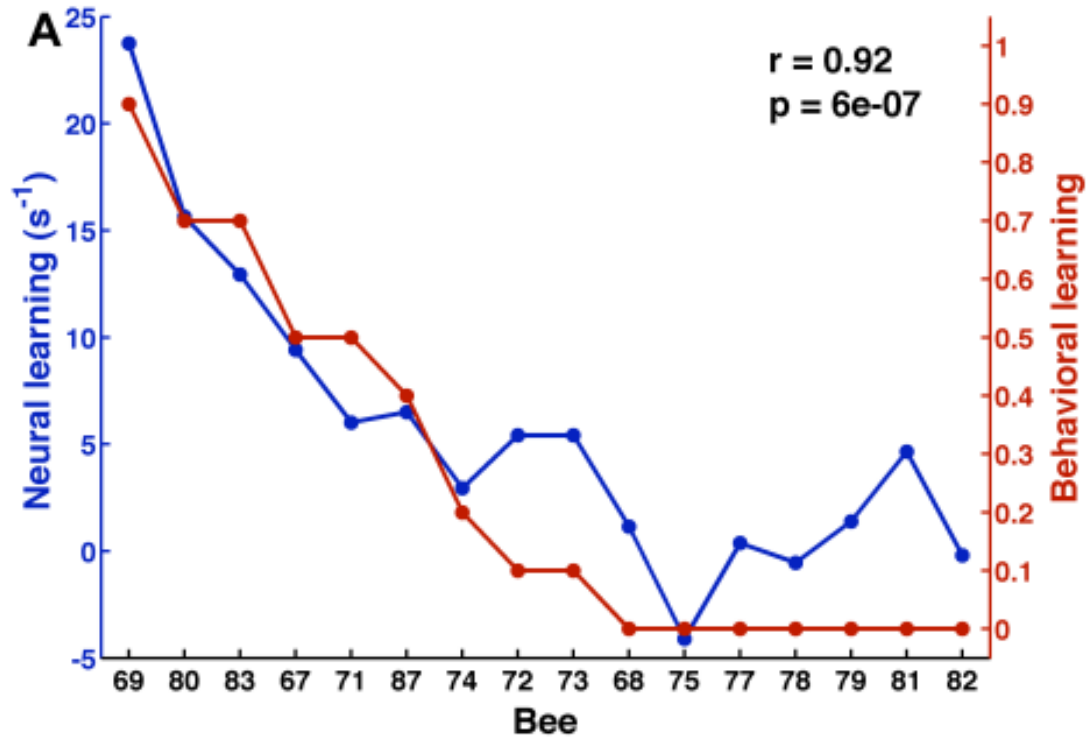


Odor VALUE coding at mushroom body output

- ▶ Reward prediction after ~ 140ms



Neural performance correlates with behavioral performance



FIN